On systemic risk formation

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The Role of Risk Spillovers, Interconnectivity and Macroprudential Policy

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Publisher: University of Groningen, Groningen, The Netherlands

Printed by: Ipskamp Drukkers BV, Enschede

ISBN: 978-90-367-7480-2 / 978-90-367-7479-6 (ebook)

On Systemic Risk Formation

The Role of Risk Spillovers, Interconnectivity and Macroprudential Policy

PhD Thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. E. Sterken
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Thursday 18 December 2014 at 09.00 hrs.

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Acknowledgements

Like the period following the asteroid Chicxulub's impact the recent Global Financial Crisis of '07/'08 gravely affected a contemporary financial type of Behemoth. Twenty years ago I would have loved to study the times prior to the former event. However, during the past four years I have had the pleasure and opportunity to research the latter, while being supported by the best colleagues, friends and family I could wish for.

First and foremost, I want to thank my supervisory team: Prof. Michael Koetter, Prof. Kasper Roszbach and Dr. Lammertjan Dam. Thank you for your guidance, keen insights, and expertise during the various stages of the PhD. Some of the main lessons I learned are to navigate between questioning and answering, and not to underestimate a project's home stretch.

The efforts of the reading committee are gratefully acknowledged. Prof. Reint Gropp, Prof. Robert Lensink and Prof. Casper de Vries, your careful reading of the manuscript is much appreciated and has resulted in valuable comments that I take to heart and helped me to improve this text.

I would like to thank the members of the department for hosting me as a PhD student and for providing a stimulating research environment. Especially Prof. Rob Alessie, Prof. Paul Bekker and Prof. Ruud Koning were prepared to help me out with questions of an econometric nature. Additionally, Paul introduced me to the Chinese class of Wing and the technology to study the language efficiently, 非常感谢. Special thanks go to Michael Wedow at the Deutsche Bundesbank and to the fellow interns there during my stay. For various reasons I also want to thank Chen Wen, Peter Dijkstra, Marco Haan, Pim Heijnen, Allard van der Made, Aljar Meesters, Jochen Mierau, Diego Ronchetti, Anna Samarina, Gaaitzen de Vries and Eelco Zandberg.

Special thanks also go to my roommates Martijn Paping and Silke Buhmann. I concur with Tomek's experiences related to room 855. Our discussions with Bernard Boonstra have indeed been memorable (Katzur, 2013). The gatherings with colleagues Nikita Bos, Rick Holgens, Wim Siekman, Xu

Yan, Vaiva Petrikaite, and Rick Holgens are always refreshing events. Some extraordinary gentlemen are also dully noted for reaping with me the side benefits of the digital network, but the members shall remain anonymous.

At parties it can be hard to motivate the pursuit of a PhD. My friend Pieter would then usually come to the rescue: "Compared to us, he suffers from learning difficulties and requires some more years to understand." To Marije, Aaltje and Femke I apologise for having been a stranger at times, but I know that buying you guys a beer usually does the trick to make amends. I fondly recall the bruises granted by Yftinus in the dojo, and running with Henry our business Zeno which we quit to pursue our post-graduate studies. The trip with Wesley was most impressive and rightly timed, thanks for that. A thank you goes at this point to all other friends and people who supported me but I fail to mention by name, safe for a few.

A warm thank you to some colorful people in Romania. In particular, I want to thank Mirela, Stelian, Elena, Alex, the young Matei, Tata Nelu and Gufu for sharing their immeasurable hospitality which is so welcoming and warm. Between Carpathian mountains we ate the best foods, cracked jokes, and competed in games during all four seasons. The invigorating times spend in Buşteni remain cherished memories of kindness.

Irina, I want to extend my gratitude to you for being you and for the wonderful years we have spend together. I remember our humor, your support and all other special moments. Throughout you have been an anchor of serenity and managed to open me up and calm me down.

Gratitude goes to my parents Pietrik and Tjeerd, brothers Jelmer and Sybrand, and their companions Tessa and Nynke. You prefer these phrases to be short, so let it suffice to say that I find it always a joy to return to Wommels to relax, to catch up with you guys, and to set a Cuban on fire.

Tali, without you having occasionally saved my life towards the end of this PhD this book may never have been finished. Our climbing adventures are also most enjoyable. It is a joy to be in the presence of your sparkling personality and I am looking forward to future quests.

Jakob Bosma

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Chapter 1

Introduction

Since the recent Global Financial Crisis that led in August 2007 to the concerted liquidity provision by a number of central banks, the concept of systemic risk received considerable attention from the academic community, policy makers and the public at large. The formation of systemic risk can be regarded as an accumulation of risks associated with the loss from some catastrophic event with the potential to collapse an entire financial system. Academics have been concerned with defining systemic risk as a concept and investigate issues of measurement. Policy makers take an interest in the problem of curbing agency problems associated with systemic risk formation and the role of regulation therein. The public has been concerned with issues of fairness and the substantial bailout funds deemed necessary by regulators to be channeled to the financial sector to maintain financial stability. This dissertation comprises a collection of four studies in the area of systemic risk formation that are both empirical and theoretical and relate to the above-mentioned concerns. All four studies are linked to the theme of systemic risk formation, but approach the topic from different angles.

Chapter 2 gives rise to the notion of *too-connected-fail* and presents extreme value theory methods to infer unobservable connections between financial institutions from joint substantial movements in credit default swap spreads and equity returns. Estimated pairwise co-crash probabilities identify significant connections among up to 186 financial institutions prior to the crisis of 2007/2008. We show that highly connected financial institutions were more likely to to be bailed out during the crisis. This result remains intact also after controlling for too-big-to-fail considerations, systematic, as well as idiosyncratic risks.

In Chapter 3 the subject of study is the impact of compensation of bank executives prior to the Global Financial Crisis on the formation of systemic risk during the crisis. Results indicate that for 92 financial institutions in the U.S., cash bonus shares and equity stakes of CEOs correlate significantly with a set of systemic risk measures. Most notably is the result that higher pre-crisis bonuses for *non*-CEO board members increased systemic risk taking according to various systemic risk measures. This effect diminishes over time after the first concerted liquidity provision by central banks in August 2007. Results are insensitive to differences in corporate governance indicators, imprinting conditions, and compensation gaps between CEOs and non-CEOs. We attribute this finding to the notion that not all layers of management, even at the executive level, share the same incentives. Backed by results earlier found in the literature in different studies, the results seem to suggest that managers are primarily concerned with the idiosyncratic performance of the division or department where they stand at the helm. If managers are not sufficiently concerned with the overall performance of the firm, and the CEO is unable to incorporate these incentives in managers' compensation scheme, the firm may take on excessive risk due to inefficient decision making.

In Chapter 4 two policy instruments for the banking sector are subject of investigation: systemic risk taxation and constructive ambiguity about bailout policy. Bailout expectations can induce moral hazard in the form of excessive risk taking by banks. Constructive ambiguity generates uncertainty about bailout prospects. At first sight it seems that systemic risk taxation induces banks to prefer uncorrelated investments, leading to lower systemic risk formation. However, systemic risk taxation may inform banks about the regulator's objective to ensure financial stability and thereby its bailout policy. Results indicate a trade-off between systemic risk taxation and constructive ambiguity, which highlights the importance to consider policies' interdependence when evaluating their effectiveness.

In Chapter 5 I present an investigation of whether and to what extent financial institutions benefitted, prior to the Global Financial Crisis, from implicit guarantees irrespective of whether they were an actual member of a formal safety net. In general, financial institutions are more likely to receive bailout support if deemed for instance *too-big-to-fail* or if they fail when many others are about to. The prospect of receiving bailout support may result in funding advantages for firms otherwise considered to be too risky. The nature of these funding advantages is modelled in the paper as an implicit guarantee. Results suggest that these implicit guarantees are likely to exist and model validation tests indicate that estimated levels of implicit guarantees indeed relate to future bailouts. The costs associated wiith these guarantees is substantial and is estimated to comprise of around twenty percent of the face value of a financial institutions' liabilities.

Chapter 2

Too connected to fail? Inferring network ties from price co-movements

2.1 Introduction

Since the Global Financial Crisis of 2007/2008, regulators and academics agree that systemically important financial institutions (SIFIs) deserve additional supervisory scrutiny given their pivotal role in the functioning of the financial system. Freixas and Rochet (2013) argue that an international prudential regulator with a far-reaching mandate to tax systemic risks and discipline SIFI management is needed instead of national authorities. Contemporary regulation does not follow these suggestions literally. However, the introduction of a Single Supervisory Mechanism in the European Union and the systemic capital charges under Basel III (2013) underscore the objective to account for systemic risk in future regulation.

Which financial institutions are systemically relevant? In addition to the

This chapter is based on joint work with Michael Koetter and Michael Wedow, published as a Deutsche Bundesbank Working Paper (Bosma et al., 2012).

sheer size of financial institutions, already Eisenberg and Noe (2001) emphasized the importance of network connections to assess the systemic risk of financial institutions and systems. The Bank of International Settlements (2013) lists accordingly the interconnectedness of financial institutions as an important (co-)determinant of a SIFI. However, a very practical challenge continues to be the inherent unobservability of connections (see Upper, 2011; Ceruttie et al., 2012).[1]

We suggest in this paper to *infer* interconnectedness from the joint likelihood of extreme credit and equity price movements between many global financial institutions from various sectors *prior* to the crisis. In an attempt to validate our inferred measures of interconnectedness, we argue that observed bailouts during the financial crisis of 2007/2008 reveal which financial institutions were considered SIFI's by policy makers. To this end we pursue a three-step procedure.

First, we use Extreme Value Theory (EVT, Hartmann et al., 2004a) to estimate so-called co-crash probabilities (CCP). CCPs measure the likelihood of an extreme joint deterioration in CDS spreads or equity prices for pairs of financial institutions. The former gauge credit risk links in the network of global financial institutions to the extent that CDS spreads reflect market participants' expectations of credit defaults (see, for example, Duffie, 2010; Giesecke and Kim, 2011; Knaup and Wagner, 2012). The latter capture the argument in Acharya (2009) and Wagner (2011) that shocks to a common exposure lead to a joint deterioration of market value of equity for all financial institutions (see De Jonghe, 2010; Ibragimov et al., 2011, for empirical applications).

Second, we identify *significant* connections between financial institutions based on pairwise CCPs *before* the crisis with a bootstrap method. Based on these significant CCPs we then generate measures of network centrality to identify connected institutions, i.e. SIFIs. Thereby, we curb the notorious

[1] Empirical work on systemic risk due to contagion in networks of financial institutions is usually confined to only banks in a single country. Some fairly early examples are Upper and Worms (2004) (Germany) and Elsinger et al. (2006) (Austria). The focus on banks fails to gauge the complexity and global scope that according to the BIS (2013) defines SIFIs.

unobservability of network ties among financial firms by both regulators and market participants alike.

Third, we test if these inferred interconnectedness indicators correlate with observable policy choices. We use connectivity indicators to predict observed bailouts *during* the crisis of 2007/2008. Bailouts are defined as capital injections and asset support measures issued by governments to rescue distressed banks that have been collected by Stolz and Wedow (2010). We argue that these observed policy actions reveal the systemic importance assigned by regulators to these banks.

We are neither the first to use EVT to measure extreme joint movement of equity returns (see, for example Longines and Solnik, 2001; Hartmann et al., 2004a) nor are we the first to use CDS prices for the measurement of contagion as one dimension of systemic importance (Jorion and Zhang, 2009; Duffie, 2010). However, to the best of our knowledge, this paper is the first to suggest a practical indicator of financial institutions' interconnectedness and relates it to observed policy choices revealing the regulator's assessment of individual institutions systemic (perceived) importance.[2]

We find "League" tables of connectivity based on network centrality measures that rank a number of arguably important banks as central according to both equity and CDS-implied network interconnectedness (e.g. Lehman Brothers, Bear Stearns, or Commerzbank). However, rank-order correlations across different types of network centrality and CDS- versus equity-based rankings are relatively low, namely in the order of around 28%. Hence, the network importance of potential SIFIs should be assessed according to both implied credit and equity connections. Logit regressions confirm that higher pre-crisis network centrality of a financial firm increases the likelihood of a government bailout after controlling for the idiosyncratic risk and size of the firm. Importantly, the sheer number of connections in both

[2] A plethora of innovative systemic risk measures has been developed recently, such as marginal expected capital shortfall in Acharya et al. (2012) or ΔCoVaR of Adrian and Brunnermeier (2011). Our approach differs to the extent that we explicitly seek to infer the interconnectedness of individual financial institutions beyond banks without imposing substantial structure on any data a priori.

CDS and equity markets bear little explanatory power for bailouts during the crisis. Especially financial firms that are important gatekeepers in connecting not many, but other central players in financial markets with another were more likely to receive bailouts.

2.2 Data on CDS spreads and stock price returns

We gauge the role of connectivity for systemic risk by estimating the likelihood of a simultaneous and drastic deterioration of the financial condition for any pair of financial firms. Such a so-called co-crash probability (CCP) can result from direct counter-party risk when an obligor fails to meet its obligations to the creditor, or through joint asset exposures to common deteriorating factors that wipe out equity. Therefore, we use both data on the joint occurrence of extremely negative equity returns as in Hartmann et al. (2004a) and De Jonghe (2010) as well as extremely positive changes in CDS spreads similar to Jorion and Zhang (2007) and Jorion and Zhang (2009).

Note that we remain deliberately agnostic as to the reasons for drastic joint deterioration of financial firm value because we argue that neither market participants nor regulators usually *observe* all potential contagion channels.[3] Instead, we present below a method how to estimate CCPs from either equity return or returns on CDS spreads.

We obtain CDS spread data from the Markit Group for the period January 2004 through January 2011.[4] We use here, however, only the pre-crisis period data between January 1, 2004 and August 8, 2007. The end date of the period is marked by the first concerted liquidity provision by central banks around the globe. Our objective is to test whether *pre-crisis* indicators of interconnectedness correlate significantly with revealed policy actions during the crisis. In order to validate whether our inferred indicators coincide with regulators assessment of financial firms' importance for the entire system.

[3] Granger-causality tests conducted in an earlier version of this paper underpinned the inconclusiveness regarding the directionality of contagion based on raw equity returns and CDS spread changes alone.

[4] See Stulz (2010) for a comprehensive review of CDS contracts and markets.

The sample consists of quotes contributed by more than 30 dealers for all trading days during the period. Markit screens these quotes and removes outliers as well as stale observations. Only when more than two contributors remain, Markit calculates a daily composite spread. CDS spread quotes are the most widely used source of CDS data in the literature (Mayordomo et al., 2013).[5] After culling the data, we end up with CDS spreads for 186 financial firms. We obtain stock price data for 164 institutions from the Bloomberg database. These data are adjusted for stock splits and cover the same sample period.

Table 2.1 shows below descriptive statistics on CDS spreads and stock price returns by financial sector and region. Most financial institutions are banks, followed by insurance companies, trusts, and intermediaries from other sectors of the financial industry. Banks exhibit the lowest mean (and median) CDS spreads during this pre-crisis period from January 1, 2004 until August 8, 2007. Insurance companies and financial firms from other sectors are in turn significantly more risky as reflected by higher mean (and median) CDS spreads. The standard deviation of stock price returns across sectors is not statistically different across financial sectors. Therefore, the credit risk measured by CDS spreads appears to gauge a different aspect of potential connectivity compared to the risk embedded in equity returns, which may rather reflect common asset exposures (see, for example Acharya et al., 2012).

From a geographical perspective, financial firms from Europe and the US account for about 80 percent of sampled institutions in terms of both CDS spreads and stock price returns. The remainder is from other developed (O.D.) and emerging market (E.M.) economies.[6]

[5] We use CDS spreads of contracts with a maturity of five years, which are most liquid. Where needed, we choose the currency with the potentially highest liquidity, usually US dollars or Euros. We selected the CDS spreads based on the ex-restructuring clause for institutions from North America, modified-modified restructuring for Western Europe, and old restructuring for Asia.

[6] See Table 2.A.1 for a list of countries per region.

Table 2.1. **Descriptive statistics: CDS spreads and stock price returns**

Sector/Region	Mean	SD	Obs.	N	Min	P25	P50	P75	Max
CDS spreads (bp)									
Sector									
Banks	18.4	16.1	106,479	118	3.3	10.1	14.0	21.2	417.3
Insurance	46.4	88.3	30,441	33	4.8	15.1	24.3	38.2	981.5
Investment Trusts	41.6	22.9	19,041	21	5.7	29.0	38.2	49.2	353.2
Other institutions	46.0	73.0	12,707	14	6.4	18.7	28.2	40.3	540.0
Region									
U.S.	35.7	31.1	52,547	57	4.8	19.8	28.5	41.1	512.2
Europe	19.4	32.0	83,173	92	3.3	10.0	13.6	19.8	540.0
O.D.	38.3	91.0	26,280	29	3.9	10.2	15.8	32.5	981.5
E.M.	38.1	24.6	6,668	8	10.9	22.5	30.0	44.6	207.0
Total	28.1	46.9	168,668	186	3.3	11.3	17.7	30.3	981.5
Stock price returns (%)									
Sector									
Banks	-0.1	1.5	95,772	109	-28.2	-0.8	0.0	0.7	27.0
Insurance	-0.0	1.4	23,632	27	-16.3	-0.7	0.0	0.7	18.2
Investment Trusts	-0.1	1.4	17,595	20	-8.8	-0.9	-0.1	0.7	18.4
Other institutions	-0.1	1.5	6,908	8	-20.0	-0.9	-0.1	0.7	16.9
Region									
U.S.	-0.0	1.3	41,710	48	-20.0	-0.7	-0.0	0.6	18.2
Europe	-0.1	1.3	61,741	69	-23.9	-0.7	0.0	0.6	27.0
O.D.	-0.0	1.5	19,852	23	-16.3	-0.7	0.0	0.7	17.7
E.M.	-0.1	2.2	20,604	24	-18.2	-1.2	0.0	1.0	22.2
Total	-0.1	1.5	143,907	164	-28.2	-0.8	0.0	0.7	27.0
Market index returns (%)									
MSCI World index	0.0	1.1	910	1	-7.3	-0.5	0.1	0.5	9.1

Notes: Descriptive Statistics of daily CDS spreads in basis points (bp) and stock price returns (%) are reported for the period January 1, 2004 through August 8, 2007. CDS spreads are obtained from the Markit Group databases. Stock prices are obtained from the Bloomberg databases. "Investment Trusts" consists of real estate investment trusts, and private equity investment trusts. "Other institutions" consist of financial services institutions, investment and lease firms, and subsidiary firms. "U.S." stands for United States. "Europe" for the developed countries in europe. "O.D" stands for developed countries other than the U.S. and the countries in Europe. "E.M" stands for "emerging markets". The specific countries within these four groups are listed in table 2.A.1.

2.3 Co-crash probabilities and Extreme Value Theory

We measure the *joint* probability of extreme positive CDS spread percentage changes or substantial joint negative stock price returns between all possible pairs of financial institutions with data. Denoting negative stock price returns or percentage CDS spread increases interchangeably by X_{it} for institution $i, j \in \{1, ..., N\}$ at day $t \in \{1, ..., T\}$, we write the co-crash probability (CCP) as a probability of the type:

$$\text{Prob}[X_{it} > u \cap X_{jt} > v], \quad i \neq j. \tag{2.1}$$

CCPs denote the probability that the underlying processes X_{it} and X_{jt} of institutions i and j exceed jointly the critical thresholds u and v and are as such extreme. Joint exceedance of markets' expectations about credit events in the case of CDS or extreme equity value deterioration are rare by definition.

Therefore, we employ multivariate extreme value theory to estimate the probability of the joint event. We follow Draisma et al. (2004) and define F as the common distribution of (X_{it}, X_{jt}) with marginal distributions F_i and F_j. We assume that there exist normalising constants a_n, $c_n > 0$ and $b_n, d_n \in \mathbb{R}$ such that we can define the CCP between firm i and j formally as:

$$\begin{aligned} CCP_{ij} &:= \lim_{T\to\infty} F^T(a_n x_i + b_n, c_n x_j + d_n) \\ &= \lim_{T\to\infty} \text{Prob}\Big(\frac{\max\{X_{i1}, ..., X_{iT}\} - b_T}{a_T} \leq x_i, \\ &\qquad\qquad \frac{\max\{X_{j1}, ..., X_{jT}\} - d_T}{c_T} \leq x_j\Big) \end{aligned} \tag{2.2}$$

The semi-parametric approach of Ledford and Tawn (1996) , and Draisma et al. (2004) to estimate Equation (2.2) allows specifically to infer (in) dependence between the underlying processes X_{it} and X_{jt}.[7] Dependence implies the existence of a connection between two institutions as reflected by extreme equity return and/or CDS spikes. Thus, we gauge connections in terms of shared risks from the perspective of debt and equity market participants without observing any such structural ties.

[7] See also Poon et al. (2004), Hartmann et al. (2007), Straetmans et al. (2008), and De Jonghe (2010). Dependence, or more precisely asymptotic dependence, implies that Equation (2.2) does not tend to zero as the sample size grows large. Asymptotic independence implies that Equation (2.2) tends to zero for a large sample size. We develop a bootstrap technique to test for dependence in subsection 2.3.3.

2.3.1 A gauge of dependence between extremes: the tail index

To extract information on the dependence between the maximum values of the two series, one needs to address the biasing impact of the marginal densities on the joint probability estimate. Therefore, we follow the semi-parametric approach of Draisma et al. (2004) and Drees et al. (2004), which only involves the estimation of the tail index η of a univariate Pareto marginal distribution to infer dependence of the extreme values of two series. The approach consists of two steps.

First, we transform the underlying processes X_{it} and X_{jt} to unit Pareto marginals. This ensures that the marginal distributions of the series have no impact on the estimated dependence between the two series' maxima (Draisma et al., 2004). Thus, differences in the estimated tail index are only attributed to differences in the dependency of extreme percentage changes in the underlying processes. We denote the unit Pareto marginal transformation of the series by $\tilde{X}_{it} := (n_i + 1)/(n_i + 1 - R(X_{it}))$, where n_i is the number of observations of institution i and $R()$ returns the rank of the argument in ascending order. Between any two institutions, the transformed series $\tilde{X}_{it}$ and $\tilde{X}_{jt}$ have the same density. Therefore, the critical threshold values q are the same across institutions and the type of probabilities (2.1) that represent the CCP can be rewritten as:

$$\begin{aligned} \mathrm{CCP}_{ij} := \mathrm{Prob}[X_{it} > x_j \cap X_{jt} > x_i] &= \mathrm{Prob}[\tilde{X}_{it} > q \cap \tilde{X}_{jt} > q] \\ &= \mathrm{Prob}[\min\{\tilde{X}_{it}, \tilde{X}_{jt}\} > q]. \end{aligned} \tag{2.3}$$

Note that the multivariate probability is now transformed into a univariate probability. This transformation permits the use of standard maximum likelihood (ML) techniques to estimate a generalized Pareto distribution for the minimized series

$$Z_t := \min\{\tilde{X}_{it}, \tilde{X}_{jt}\}. \tag{2.4}$$

For notational convenience, the subscripts i and j are dropped for Z_t. Suppose that two institutions exhibit a perfect connection and as a result their transformed underlying processes $\tilde{X}_{it}$ and $\tilde{X}_{jt}$ move identically in terms of unit Pareto marginal rankings. Then Z_t equals the transformed variable $\tilde{X}_{it}$ and its density exhibits a unit tail index by construction. If such co-movement does not exist, the minimized series Z_t exhibits a minimal fat tail and the tail index of its density is smaller than one. We use this feature below to test for whether their exists a risk connection between two institutions. A tail index estimate close to one, indicates that two institutions experience the largest movements in the underlying processes on any given day, whereas a tail index estimate smaller than one shows the opposite.

Thus, the extent to which institutions are credit- or equity-risk connected can be represented by the estimated value of the tail index of the generalized Pareto density of the minimized series Z_t. We use Hill's (1975) ML technique to estimate the tail index η, which is denoted by:

$$\hat{\eta}(k) := \frac{1}{k}\sum_{m=1}^{k} \ln\Big[\frac{Z(n-m+1)}{Z(n-k)}\Big]. \tag{2.5}$$

A typical problem in calculating the Hill estimator in Equation (2.5) is the nontrivial choice of k: the sample of "large" values in the joint underlying series that proxy for the arrival of credit or equity risk events, i.e. large positive movements in the underlying processes. If k is too small, too few observations enter the estimation of the tail index to ensure consistent estimation of the index. In contrast, too high levels of k result in a biased tail index estimate because larger number of observations enter the estimation that originate from the central mass of the distribution and do not represent tail events. The decision on the optimal number of observations to estimate Equation (2.5), k^*, thus represents a variance-bias trade-off between a too high variance of the estimator for low values of k versus a lower variance for large values of k which have the potential to introduce bias.

We follow Huisman et al. (2001) to determine k^* and approximate the bias in estimating the tail index to be linear in k.[8] The bias is a linear rela-

[8] Alternatively, one can plot Equation (2.5) for different k, evaluate the range of tail index

tionship between the estimated tail index and the number of observations included for estimation:

$$\hat{\eta}(k) = \gamma_0 + \gamma_1 k + \varepsilon_k, \quad \forall k \in \{1, ..., n-1\}, \tag{2.6}$$

where ε_k denotes a random noise term and the coefficient parameters γ_0 and γ_1 characterize the bias relationship between the tail index estimate (2.5) and the number of observations included for its computation. Like Huisman et al. (2001), we estimate the bias approximation (2.6) with weighted least squares using weights proportional to $\sqrt{k}$ to obtain unbiased and consistent estimates of $\hat{\gamma}_0$ and $\hat{\gamma}_0$. This procedure assigns less weight to the tail index estimates in the region where they are least consistent, which is likely to be the case for low values of k. The unbiased estimate of the tail index is obtained from $\hat{\gamma}_0$, which is substituted in Equation (2.5) to determine k^*

We choose k by minimizing $(\hat{\eta}(k) - \hat{\gamma}_0)^2$. The k that minimizes this sequence in a stable area is denoted as k^*.[9] Substitution of k^* in (2.5) yields the tail index estimate of the two series of percentage changes in CDS spreads.

Table 2.2 summarizes the percentage changes in CDS spreads for the 186 sampled financial institutions in the periods before August 8, 2007. In addition the table reports the critical returns of the sampled 164 institutions' stock prices. The cutoff day marks the initiation of the first major public interventions by central authorities due to the Global Financial Crisis. To alleviate market concerns about widespread exposures of financial institutions to U.S. subprime mortgage lending markets, the ECB provided low-interest credit lines of USD 130 billions. The Federal Reserve followed suit with USD 12 billions in temporary reserves. Therefore, we consider only the pre-crisis period until August 9, 2007 to infer interconnectedness from significant CCPs. Additionally, summary statistics of the percentage changes in CDS spreads and negative stock price returns that have been included for

estimates that are stable across k, and choose k^* in a region with minimal tail indeces. Alternatively Danielsson et al. (2001) provide a double bootstrap procedure to determine k^*.

[9] We do a grid search to choose k^* in an area where neighboring k values also yield squared prediction errors sufficiently close to zero to avoid obtaining an accidental k^* in an area where $\hat{\eta}$ is inconsistent.

Table 2.2. **Extreme changes in CDS spreads and stock prices**

CDS changes in pct./ PCTL	Mean	SD	Obs.	Min	P25	P50	P75	Max
CDS spread pct. changes								
Overall sample	0.15	4.58	158,695	-169.93	-0.59	0.00	0.51	211.95
Critical changes only	2.29	4.68	71,361	0.00	0.26	0.93	2.45	209.58
PCTL of critical changes	87.91	7.74	17,561.00	39.88	81.86	88.46	94.72	100.00
Stock price returns								
Overall sample	-0.12	1.51	143,907	-28.20	-0.83	0.02	0.70	27.02
Critical changes only	-0.93	1.07	72,188	-28.20	-2.12	-0.65	-0.12	-0.05
PCTL of critical changes	86.73	8.85	13,809	63.74	80.35	88.41	94.15	100.00

Notes: Top two rows for of the two categories report descriptive statistics on percentage changes in the underlying series, both for the overall sample and for the critical changes that are included in the calculation of the Hill estimator, (2.5). The total number of observations differ from Table 2.1 because of an unbalanced panel. The last row of each category reports statistics of the percentiles of the minimum percentage change in CDS spreads included for estimation of the tail index, as outlined in section 2.32.3.1 The considered sample period for estimation purposes runs from January 1, 2004 through August 8, 2007.

estimating the CCPs are reported.

On average we only use observations for estimating the tail index that are above the 87^{th} and 86^{th} percentile respectively for the joint CDS change series and for negative stock price returns, as indicators for extreme movements. It is important not to confuse the percentiles in Table 2.2 with those specified in Value-At-Risk based approaches to calculate "extreme" events, since the critical cutoff value that denotes extreme is not imposed by the researcher. Instead, the Huisman et al. (2001) method determines the optimal sample size to calculate CCPs in light of the consistency-bias tradeoff faced when estimating the tail index.

2.3.2 Co-crash probability estimation

Draisma et al. (2004) extend Ledford and Tawn (1996) and develop an estimator for the probability of an extreme event as denoted by (2.2) that allows for both asymptotic dependence and independence between two series. This semi-parametric estimator requires no assumptions about the specification for the joint density of the underlying processes X_{it}. However, a marginal density is required to be defined. To this end, let the maximum of X_{it} follow the generalized Pareto distribution with shape parameter ξ_i, scaling parameter a_i, and location parameter b_i, such that the cumulative density of X_{it} is denoted by

$$F_i(x) := 1 - \left(1 + \xi_i \frac{x - b_i}{a_i}\right)^{-\frac{1}{\xi_i}}. \tag{2.7}$$

Parameters are estimated with ML techniques and calculated for each institution separately. Thus, heterogeneity with respect to idiosyncratic failure probabilities is preserved. Parameter estimates are denoted by $\hat{\xi}_i$, $\hat{a}_i$, and $\hat{b}_i$.

Let $\hat{F}_i$ be specified as (2.7) with parameters replaced by estimates. Let $\hat{\boldsymbol{F}}_{ij} := (\hat{F}_i, \hat{F}_j)$, a two-dimensional vector with elements reflecting the idiosyncratic probabilities of non-extreme events for both institutions, for example percentage changes in CDS spreads are smaller than the critical levels of institutions i and j. Similarly, $\hat{\boldsymbol{F}}_{ij}^{-1} := (\hat{F}_i^{-1}, \hat{F}_j^{-1})$. This term identifies the values of the underlying process that are larger than the thresholds implied by the Huisman et al. (2001) method discussed earlier. Last, let $\boldsymbol{D}_{ij} := (1 - \hat{F}_i, 1 - \hat{F}_j)$ a row vector with probabilities of the event in which both institutions' CDS spread percentage changes exceed their critical thresholds. The estimator of CCP, (2.2), is denoted by:

$$\widehat{\mathrm{CCP}}_{ij} := c_{ij}^{1/\hat{\eta}_{ij}} \frac{1}{n_{ij}} \sum_{t=1}^{n_{ij}} \mathbf{1}\big\{(X_{it}, X_{jt}) \in \hat{\boldsymbol{F}}_{ij}^{-1}(\boldsymbol{\iota} - \boldsymbol{D}_{ij}/c_{ij})\big\}. \tag{2.8}$$

The operator $\mathbf{1}\{.\}$ returns a 1 if the condition in braces is fulfilled and a zero if not: a 1 indicates the occurrence where both institutions face an extreme event, and 0 that they do not. The operand $\{(X_{it}, X_{jt}) \in \hat{\boldsymbol{F}}_{ij}^{-1}(.)\}$ identifies the set of CDS spread percentage changes that are larger than the critical values returned by $\hat{\boldsymbol{F}}_{ij}^{-1}(.)$. Hence, the summation over the sampled days, n_{ij}, yields the number of observations for which both institutions experience contemporaneously a detrimental credit event.

The constant $c_{ij} \in (0, 1]$ inflates the set of critical exceedance values. Note that for smaller values of c_{ij}, the critical levels in $\hat{\boldsymbol{F}}_{ij}^{-1}(.)$ are larger, i.e. more extreme. Smaller values of c_{ij} essentially imply a reduction in the number of observations for which both institutions experience simultaneously a detrimental credit event. Because the domain of $\hat{\boldsymbol{F}}_{ij}^{-1}(.)$ is $[0,1] \times [0,1]$, the choice of c_{ij} is limited to $(\max\{\boldsymbol{D}_{ij}\}, 1]$. We determine c_{ij} by evaluating $\widehat{\text{CCP}}_{ij}$ as a function of c_{ij}, and choose the minimal value of c_{ij} for which $\widehat{\text{CCP}}_{ij}$ is sufficiently stable (Draisma et al., 2004).[10]

2.3.3 Inferring extreme risk connections from the tail index

Draisma et al. (2004) investigate the asymptotic properties of the tail index estimate $\hat{\eta}_{ij}$ as defined by the Hill estimator (2.5) and find that the estimate exhibits asymptotic normality as the number of observations becomes large. This result motivates the use of a bootstrap procedure to obtain a standard error of $\hat{\eta}_{ij}$ for the purpose of developing a statistical test to infer dependence between extreme credit events of two institutions. We employ the stationary bootstrap procedure suggested by Politis and Romano (1994) to allow for weakly dependent observations in the underlying to calculate the standard error of the tail index estimate in Equation (2.5). The bootstrap procedure consists of the following steps:

1. A tail index estimate $\hat{\eta}_{ij}$, (2.5) is calculated along the lines of the estimation technique described in subsection 2.3.1

2. For each of the B bootstrap replications the underlying processes X_{it} and X_{jt} are resampled in blocks of consecutive observations of random block length to yield a bootstrap sample X_{it}^{b} and X_{jt}^{b} of equal length as the original sample, where b indexes the b^{th} replication.[11] From these bootstrap samples B tail index estimates $\hat{\eta}_{ij}^{b}$ are generated as in step 1.

3. The bootstrap standard error of $\hat{\eta}_{ij}$ is denoted by $s(\hat{\eta}_{ij}) = \sqrt{\frac{\sum_{b=1}^{B}(\hat{\eta}_{ij}^{b} - \hat{\eta}_{ij})^2}{B-1}}$.

4. Let η_0 be the hypothesized true value of η_{ij} under the null. Then the

[10] The same grid search is adopted as in determining the optimal numbers of observations k^* in the estimation of the tail index.

[11] For one particular block the starting value and the length are chosen uniformly at random across the number of observations.

test statistic $\frac{\hat{\eta}_{ij}-\eta_0}{s(\hat{\eta}_{ij})}$ can be computed and follows a student-t distribution with $B-1$ degrees of freedom. A one-sided t-test can be conducted to gather evidence against the null of asymptotic dependence.

Dependence in large percentage changes of CDS spreads between two institutions is then determined by testing the null of dependence against the alternative of independence. In terms of the tail index value, dependence holds if $\eta_{ij} = 1$, perfect co-movement among the largest values in the underlying processes. Independence holds if $\eta_{ij} < 1$. For $\eta_{ij} = 1$ the joint crash probability converges eventually to a positive value, whereas for $\eta_{ij} < 1$ the probability converges eventually to zero. If the null is not rejected, a credit link between institutions i and j is assumed to exist. Throughout, the number of bootstrap replications is 10,000, and the significance level is one percent.

Table 2.3 reports descriptive statistics of the estimated co-crash probabilities. Note that we distinguish between all co-crash probabilities and those for which dependence in credit events could not be rejected. Since 186 institutions are sampled for which we have sufficient observations on CDS spreads, a maximum of 17,205 potential links can exist.[12] Likewise, for the stock-price based CCPs we have 13,366 connections, because we sampled 164 institutions.

CCPs are right-skewed for both stock price-based and CDS spread-based CCPs. For those CCPs for which we failed to reject asymptotic dependence the estimated size of the CCP is larger across percentiles relative to the full sample of estimated CCP. This observation shows that for institutions for which we find evidence of a credit risk connection the probability of experiencing both a spike in the underlying process is higher, which is not necessarily borne out by the method. What's noticeable is that CDS spread-based CCPs are generally larger than the stock price-based CCPs. A potential explanation for this phenomena lies in the nature of the CDS contract which is typically short term (five years for our data) and relates solely to the likeli-

[12] Each institution can share a credit connection with 185 institutions. Counting connections only once results in $\frac{186(186-1)}{2} = 17,205$ potential credit risk connections.

Table 2.3. **Descriptive statistics: Co-Crash Probabilities**

Sample covers both pre and during-crisis period

Co-crash probabilities in basis points	Mean	SD	Obs	Min	P25	P50	P75	Max
CDS spread-based CCPs								
Overall sample	5.47	5.58	17,205	0.00	2.20	4.21	7.43	71.75
Only significant CCPs*	7.19	5.88	11,785	0.00	3.69	5.90	9.15	71.75
Stock price-based CCPs								
Overall sample	2.21	2.18	13,366	0.00	0.93	1.73	2.94	27.67
only significant CCPs*	5.32	2.61	2,595	0.00	3.54	4.77	6.59	27.67

Notes: Co-crash probabilities are reported in basis points. '*' indicates that only statistics are reported for co-crash probabilities between two institutions that share a common 'credit-risk link'. For these co-crash probabilities, the tail index is not significantly different from one at the 1%-significance level. The number of observations reflect the number of co-crash probabilities estimates for any possible combination of two institutions in the sample. Since 186 institutions are investigated with respect to the CDS spread-based CCPs, the total number of co-crash probabilities per period amounts to $186(186-1)/2 = 17,205$. Likewise, the total number of possible ties for the Stock price-based CCPs amounts to $13,366$, based on 164 institutions.

hood of a credit risk event. Whereas stocks prices relate both to short as well as long term profitability prospects and movement in prices do not necessarily only concern credit events.

2.4 Connectivity

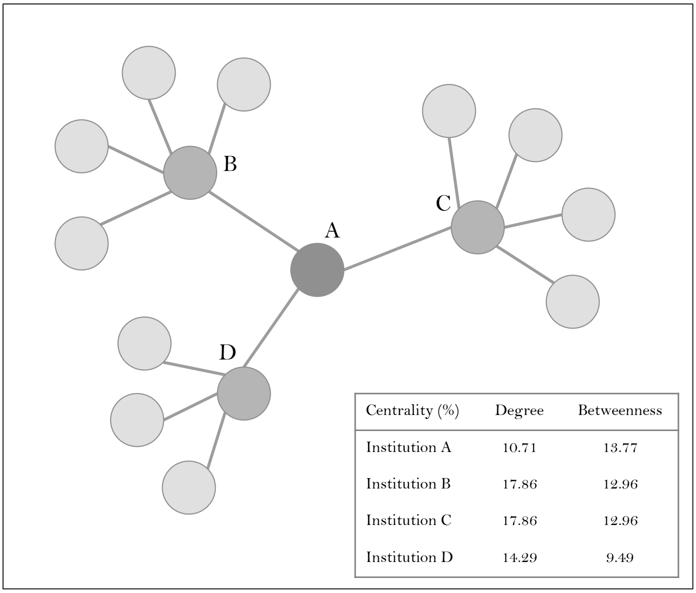
Based on significant CDS and equity-based CCP links, we identify next those financial intermediaries that take central positions in the financial sector. To this end, we define the nature of centrality for the example of credit-risk connectivity.

2.4.1 SIFI identification based on network centrality

Jorion and Zhang (2007) define credit risk contagion as a directional phenomenon. One institution's credit event has a direct impact on the credit position of institutions with which it shares a substantial correlation in CDS spread percentage changes. In our study direct credit contagion between two institutions is reflected by those CCPs for which we fail to reject the null that both of the underlying processes are asymptotically dependent. An important difference to Jorion and Zhang (2007) is that we remain agnostic with respect to the direction of effects. This feature of our CCP measure is important because ultimately neither we nor market participants and regulators observe existing credit ties and shocks. We thus rely on the observable yet very rare occurrence of joint extreme movements.

Credit risk shocks can be transitive when one institution's credit event affects negatively the credit position of another institution via a third institution rather than directly. The finding of Arora et al. (2012) that counterparty credit risk of dealer firms is priced in CDS spreads of other institutions serves as an argument for such indirect credit risk effects. The failure and rescue of AIG, a major seller of CDS protection, further illustrates the importance of indirect connections via a protection seller to policy makers. AIG was not central in terms of many credit links with other institutions in the financial system. But it connects large clusters of other agents which are not directly connected. Figure 2.1 illustrates the two considered types of centrality: direct degree and "gatekeeper" betweenness centrality.

Figure 2.1. Differences in centrality



Centrality (%)	Degree	Betweenness
Institution A	10.71	13.77
Institution B	17.86	12.96
Institution C	17.86	12.96
Institution D	14.29	9.49

Notes: Figure displays 14 hypothetical financial institutions as nodes which share significant credit links. Significant credit links are displayed as edges. Degree centrality denotes the proportion of institutions with which the subject institution shares a significant credit link. Betweenness centrality represents the number of times an institution acts as key link that connects two institutions along the shortest path (Bonacich, 1972). The Betweenness centrality measure is rescaled to a percentage of the total number of times an institution connects two other institutions along the shortest path.

The direct degree centrality of institution A in figure 2.1 is low relative to the centrality of B and C, because A shares only with three institutions a significant credit link out of the total of 14 possible other institutions. Institution B and C seem to be the most connected based on degree centrality. However, from a "betweenness" centrality perspective, institution A connects the large hubs with institutions B and C at their respective centres. This feature renders institution A central in the gatekeeper sense.

We measure the connectivity of financial institutions in the network represented by significant credit and equity risk links. First, we assess how the institutions are connected in the overall financial system. CCPs for which we do not reject the null of a tail index equal to one indicate the strength with which two institutions are linked (see Section 2.3.3). A simple measure for the network centrality of an institution is the ratio of the number of CCPs for which tail dependence could not be rejected and the number of institutions in the sample except for the institution in question. Let l_{ij} denote a credit link variable that takes a value of 1 if dependence is found between the institutions' percentage changes in CDS spreads or negative stock price returns. Let I denote the total number of institutions present in the sample. Following Jackson (2010), degree centrality is denoted by:

$$degree_i = 100\% \times \frac{1}{I-1} \sum_{j \in \{1,\ldots,I|j \neq i\}} l_{ij}, \tag{2.9}$$

and ranges from zero to one hundred percent. Zero percent indicates that the institution has no direct credit links with other institutions. A value of 100 percent implies that the institution is connected to all institutions.

The betweenness centrality measure is somewhat more tedious to obtain than degree centrality. The idea is to assign high centrality to an institution that may have only significant CCPs with a few, yet important peers. This measure denotes the number of times an institution acts as key link that connects two institutions along the shortest path of credit links. In this context, Bonacich (1972) proposes to take the centrality of an institution to be proportional to that of its neighbors. Let C_i denote such a measure for institution i and λ an arbitrary scaling value, then $\lambda C_i = \sum_{j \in \{1,\ldots,I|j \neq i\}} \widehat{CCP}_{ij} \times C_j$. Note that the centrality measures of the neighbors are weighted with the corresponding co-crash probability. To calculate the C_i values a system of linear equations needs to be solved, namely one equation for each of the sampled institution.

This approach amounts to retrieving the eigenvectors of the square symmetric matrix that has diagonal elements equal to zero and the co-crash probabilities as off-diagonal elements and the institutions index the rows and columns. Let such a matrix be denoted by $\boldsymbol{P}$ and gather all centrality measures C_i in the column vector $\boldsymbol{C}$. The system can then be stated as

$$\lambda \boldsymbol{C} = \boldsymbol{PC}. \tag{2.10}$$

Note that the solution to $\boldsymbol{C}$ denotes the eigenvector of $\boldsymbol{P}$ that corresponds to the eigenvalue λ. Typically, the associated type of centrality is often denoted as eigenvector centrality. We take the largest eigenvalue of $\boldsymbol{P}$ to ensure that the eigenvector centrality scores can be positive. The centrality measure C_i for each institution is then retrieved from the i^{th} element of the considered eigenvector. Bonacich centrality represents the number of times an institution acts as key link that connects two institutions along the shortest path (Bonacich, 1972). This Betweenness centrality measure is rescaled to a percentage of the total number of times an institution connects two other institutions along the shortest path.

To identify systemically important financial institutions, Tables 2.4 and 2.5 show the ranking of the top 40 connected financial firms according to degree centrality and Bonacich centrality based on CCPs for both CDS spread-based and stock price-based CCPs.

Table 2.4. **Institutions ranked by degree centrality**

Spearman correlation of degree centrality for the two types: 0.236***

CDS spread-based CCPs				*Stock price-based CCPs*			
Name	Country	sector	Degree centrality (%)	Name	Country	sector	Degree centrality (%)
Banco BPI	PT	Bank	99.4	Axa	FR	Insur.	53.3
DZ Bank Zentral	DE	Bank	97.8	Commerzbank	DE	Bank	52.7
Comm. W. Bank of Aus.	AT	Bank	96.7	United Overseas Bank	SG	Bank	49.6
SEB	SE	Bank	95.1	The Hartford Fin. Serv.	US	Insur.	49.6
Bank of Montreal	CA	Bank	94.5	Malayan Banking	MY	Bank	49.0
IKB	DE	Bank	94.0	Deutsche Post Bank	DE	Bank	46.6
St. George Bank	AU	Bank	92.9	Swedbank	SE	Bank	46.0
Standard Chartered	UK	Bank	92.9	Banco Espirto Santo	PT	Bank	44.7
Public Bank Berhad	MY	Bank	92.9	Hammerson	UK	IT	44.7
HSH Nord Bank	DE	Bank	92.9	Syd Bank	DK	Bank	44.7
HBOS	UK	Bank	92.4	Banco Commercial Port.	PT	Bank	44.1
Bank of Nova Scotia	CA	Bank	91.8	BBV Argentaria	ES	Bank	42.9
LBank Hessen Theur.	DE	Bank	91.3	UBS	CH	Bank	40.4
United Overseas Bank	SG	Bank	91.3	JPMorganChase	US	Bank	40.4
Mizuho Bank	JP	Bank	91.3	Anglo Irish Bank	IE	Bank	40.4
Banco Sabadell International	ES	Bank	90.8	Svenska Handels Banken	SE	Bank	39.8
ANZ Banking Group	AU	Bank	90.2	Wendel	FR	IT	39.8
Anglo Irish Bank	IE	Bank	90.2	Dexia	BE	Bank	39.2
Sompo Japan Insurance	JP	Insur.	90.2	Banco Santander	ES	Bank	39.2
Caja de a Horros de V.	ES	Bank	89.7	IVG Immobilien	DE	IT	38.6
Raiffeisen Bank Zentral	AT	Bank	89.1	Goldman Sachs	US	Bank	38.0
Prudential	UK	Insur.	89.1	Allied Irish Bank	IE	Bank	38.0
Assicurazioni Gen.	IT	Insur.	89.1	Credit Suisse	CH	Bank	37.4
Credit Agricole	FR	Bank	89.1	Wells Fargo	US	Bank	37.4
Commerz Bank	DE	Bank	89.1	IKB	DE	Bank	36.1
HV Bayerische HypoVer.	DE	Bank	88.6	Bank Mandire	ID	Bank	36.1
Aegon	NL	Insur.	88.6	Assicurazioni Gen.	IT	Insur.	35.5
Goldman Sachs	US	Bank	88.6	3i Group	UK	IT	34.9
HSBC Holding	UK	Bank	88.1	Lincoln National	US	Insur.	34.9
Aviva	UK	Insur.	88.1	Unibail Rodamco	NL	IT	34.9
BBV Argentaria	ES	Bank	88.1	Banco Sabadell Intern.	ES	Bank	34.3
BNP	FR	Bank	88.1	Deutsche Bank	DE	Bank	34.3
Swiss Reinsurance	CH	Insur.	87.5	Standard Char.	UK	Bank	33.7
HSBC Bank	UK	Bank	87.5	Irish Life Perm. Public	IE	Fin. Serv.	33.1
Unicredito	IT	Bank	87.0	Allianz	DE	Insur.	33.1
Banco Santander	ES	Bank	87.0	Jyske Bank	DK	Bank	32.5
Banca Popolare di Milano	IT	Bank	87.0	Banco Pop. di Verona	IT	Bank	32.5
Svenska Handels Banken	SE	Bank	87.0	Erste Bank	AT	Bank	31.2
Banco Espirto Santo	PT	Bank	86.4	Banco Populare Es.	ES	Bank	31.2
Banco Commercial Port.	PT	Bank	86.4	Merrill Lynch	US	Bank	31.2

Notes: Pre-crisis is the period of January 1, 2004 until August 9, 2007. Institutions are sorted in descending order by their degree centrality measure. The number of established ties over possible ties is denoted as degree centrality, and is calculated by dividing the number of significant co-crash probabilities associated with an institution through the number of institutions in the sample minus one, 192. The two characters in the country codes correspond to the ISO 3166 country codes. '***' denotes a significantly different from zero Spearman rank order coefficient at the 1%-level (Bonferroni adjusted).

Table 2.5. **Institutions ranked by Bonacich centrality**

Spearman correlation of degree centrality for the two types: 0.284***							
CDS spread-based CCPs				*Stock price based CCPs*			
Name	Country	sector	Bonacich centrality (%)	Name	Country	sector	Bonacich centrality (%)
Anglo Irish Bank	IE	Bank	99.4	Axa	FR	Insur.	98.5
BBV Argentaria	ES	Bank	95.0	Commerzbank	DE	Bank	90.8
Capitalia	IT	Bank	94.1	Deutsche Post Bank	DE	Bank	87.9
ABN Amro	NL	Bank	93.8	Banco Santander	ES	Bank	84.1
Banco Comm.l Port.	PT	Bank	90.8	Dexia	BE	Bank	82.4
Banca M.dei Paschi di S.	IT	Bank	88.8	Wendel	FR	IT	80.4
Banco Santander	ES	Bank	86.2	Swedbank	SE	Bank	78.9
Banco Espirto Santo	PT	Bank	85.3	UBS	CH	Bank	78.6
Aviva	UK	Insur.	84.7	IKB	DE	Bank	78.1
Comm. W. Bank of Aus.	AS	Bank	83.6	BBV Argentaria	ES	Bank	77.0
Aegon	NL	Insur.	82.0	Banco Pastor	ES	Bank	75.6
Swiss Reinsurance	CH	Insur.	79.0	Banco Comm. Port.	PT	Bank	75.1
Societe Generale	FR	Bank	78.0	Banco Espirto Santo	PT	Bank	75.1
Prudential	UK	Insur.	76.1	Svenska Handels Banken	SE	Bank	74.1
Credit Agricole	FR	Bank	74.3	Ageas	BE	Insur.	73.1
Banco BPI	PT	Bank	73.8	Credit Suisse Group	CH	Bank	70.8
Lehman Brothers	US	Bank	73.4	Allianz	DE	Insur.	70.0
Unicredito	IT	Bank	73.2	Banco Sabadell Inter.	ES	Bank	69.5
AIG	US	Insur.	71.5	Assicurazioni Gen.	IT	Insur.	67.6
Assicurazioni Gen.	IT	Insur.	70.0	Aegon	NL	Insur.	67.2
Royal Bank of Scotland	UK	Bank	69.8	Banco Pop. Espanol	ES	Bank	67.1
The All State	US	Insur.	69.0	BNP	FR	Bank	66.8
IKB	DE	Bank	68.5	Standard Chartered	UK	Bank	66.5
Lloyds Bank	UK	Bank	68.0	Hammerson	UK	IT	66.2
HV Bayerische HypoVer.	DE	Bank	67.3	Jyske Bank	DK	Bank	65.6
Public Bank Berhad	MY	Bank	66.2	Syd Bank	DK	Bank	65.2
Barclays Bank	UK	Bank	64.6	The Hartford Fin. Serv.	US	Insur.	65.0
Dresdner Bank	DE	Bank	64.5	Allied Irish Bank	IE	Bank	64.9
General Electir Capital	US	Bank	64.4	IVG Immobilien	DE	IT	64.8
ING Bank	NL	Bank	64.0	Wells Fargo	US	Bank	63.2
Legal General Group	UK	Insur.	63.0	Banco Pop.e di Verona	IT	Bank	62.8
Ex Im Bank China	CN	Bank	61.4	Deutsche Bank	DE	Bank	62.1
Muenchener RE	DE	Insur.	61.3	3i Group	UK	IT	61.7
MGIC Investment	US	Insur.	60.5	Credit Agricole	FR	Bank	61.6
BNP	FR	Bank	60.4	JPMorganChase	US	Bank	61.4
Goldman Sachs	US	Bank	60.4	Merrill Lynch	US	Bank	61.2
ANZ Banking Group	AS	Bank	59.5	Unibail Rodamco	NL	IT	60.7
Rabobank	NL	Bank	59.4	Medio Banca	IT	Bank	60.3
Abbay National	UK	Bank	58.9	Legal General Group	UK	Insur.	60.3
Credit Lyonnais	FR	Bank	58.7	Barclays Bank	UK	Bank	57.5

Notes: Pre-crisis is the period of January 1, 2004 until August 9, 2007. Institutions are sorted in descending order by their Bonacich centrality measure. Bonacich centrality is a measure of the influence of an institution among peer members in a financial network. It assigns relative scores to all institutions in the system based on the concept that connections to highly connected institutions contribute more to the connectivity of the institution in question than equal connections to low-scoring nodes. The measure therefore reflects the extend to which an institution is an important gatekeeper in the financial system. The two characters in the country codes correspond to the ISO 3166 country codes. '***' denotes a significantly different from zero Spearman rank order coefficient at the 1%-level (Bonferroni adjusted).

The resulting rankings highlight first of all that implied interconnectedness measured by CDS and equity return ties gauge different aspects.

For both measures of network centrality, the rank-order correlation between CDS- and return-based network centrality is significant but fairly low (23% – 28%). Hence, these league tables underpin the importance to consider multiple indicators of systemic relevance regarding the interconnectedness dimension.

Second, all four rankings are plausible to the extent that a number of banks are listed were actually rescued. Examples are IKB and Commerzbank, which appear among the 40 most interconnected banks in six out of the eight rankings shown in Tables Tables 2.4 and 2.5.

Third, a number of insurances as well as not so obvious banking firms are connected to many other financial institutions. Likewise, the regional dispersion of central financial firms is high in all rankings. Therefore, these measures indicate that effective prudential supervision of SIFIs should probably not only focus on banks. Instead, a more holistic approach to supervision that is crossing not only national borders, but also sectoral boundaries, seems warranted.

2.4.2 Implied network centrality and revealed SIFI assessment

But do implied measures of network centrality properly identify SIFIs? Whereas we cannot "validate" our agnostic CCP-based connectivity measures of systemic importance with structural data, such as for example observed interbank credit connection, we seek to test this notion more formally.

Bailouts during the crisis

To do so, we argue that a bailout of any financial institution reveals the regulators perception of that firm's systemic relevance. Numerous financial institutions were bailed out during the financial crisis of 2007/2008 in the wake of unparalleled concerted efforts of central banks and governments around the world. Many of these bailed out banks are actually among those identified as SIFIs based on network centrality represented by significant CDS co-crash probabilities. Actual bailouts under the auspices of the various national schemes, such as the Troubled Asset Relief Program in the US or the Federal Agency for Financial Market Stabilisation fund (*"Bundesanstalt für Finanzmarktstabilisierung"*) and other schemes, have been collected systematically by the European Central Bank (see Stolz and Wedow, 2010). Bailouts entail either capital injections by governmental institutions or various forms of asset support for financial institutions.[13] These data are shown in Table 2.6.

[13] More specifically, governmental institutions include federal and local governments. As a consequence measures taken outside official schemes are also included. With regard to asset support, these measure include asset guarantees and asset removal. Under the former approach, the actual assets remain on the bank's balance sheet but are insured by the government while the latter typically implied the set up of a bad bank.

Table 2.6. **Dates of first time rescue measures for financial institutions**

Name	Country	First time fin. support received	Capital injection	Asset support	Total cap. injections	Total asset support
ABN Amro	NL	07/31/09		x		1
Aegon N.V.	NL	10/28/08	x		1	
AIG	US	11/11/08	x	x	3	1
Allied Irish Bank	IE	12/12/08	x		2	
Alpha Bank	GR	01/12/09	x		2	
American Express	US	01/09/09	x		1	
Anglo Irish Bank	IE	05/29/09	x		3	
Banca Monte Paschi	IT	12/30/09	x		1	
Bank of America	US	10/28/08	x		3	
Bank of Ireland	IE	01/08/09	x		1	
Banque Pop. France	FR	06/30/09	x		1	
Bayrische Landesbank	DE	10/21/08	x		2	
BNP	FR	10/20/08	x		2	
Caisse d' Epargne	FR	10/20/08	x		1	
Capital One Fin. Corp.	US	11/14/08	x		1	
Citigroup	US	10/28/08	x		1	
Commerzbank	DE	11/03/08	x		2	
Credit Agricole	FR	10/20/08	x		1	
Danske Bank	DK	05/05/09	x		1	
Dexia	BE	09/30/08	x		1	
EBS Building Society	IE	04/02/10		x		1
EFG Eurobank	GR	01/12/09	x		1	
Erste Bank	DE	02/27/09	x		1	
Fannie Mae	US	03/02/09	x		7	
Fortis Group	NL	10/03/08	x		3	
Freddie Mac	US	11/14/08	x		5	
Goldman Sachs Group	US	10/28/08	x		1	
HSH Nord Bank	DE	05/20/09	x		1	
Hypo Real Estate	DE	03/30/09	x		6	
IKB	DE	07/27/07	x		4	
ING Groep	NL	10/20/08	x		1	
Irish Nationalwide	IE	04/02/10	x	x		1
JPMorgan Chase	US	10/28/08	x		1	
KBC Group	BE	10/27/08	x		2	
Landesbank Baden-Wurtemb.	DE	11/21/08	x		1	
Lloyds Bank	GB	01/19/09	x		2	
Morgan Stanley	US	10/28/08	x		1	
National Bank of Canada	CA	01/21/09	x		1	
Natixis	FR	05/14/09	x		1	
Nordea Bank	SE	03/12/09	x		1	
Northern Rock	GB	10/28/09	x		1	
Pireus Bank	GR	01/23/09	x		1	
RBS	GB	10/13/08	x		2	
SNS Bank	NL	11/13/08	x		1	
Societe Generale	FR	10/20/08	x		2	
Sparkasse Koln-Bonn	DE	01/01/09	x		2	
Suntrust Banks	US	11/14/08	x		2	
UBS	CH	10/16/08	x	x	1	1
US Bank Corp.	US	11/14/08	x		1	
Wells Fargo	US	10/28/08	x		1	
Westdt. Landesbank	DE	02/01/08		x		3

Table provides overview of financial support for financial institutions implemented by financial regulators. Dates are denoted by "mm/dd/yy". "Total Capital injections" and "Total Asset Support" refer to the total amount of capital injections received and asset support received in the period defined by the first time of financial support received until March 10, 2011.

The vast majority of the 51 financial institutions receiving either capital injections or asset support were banks. Bailouts were conducted in 14 different countries, illustrating the global nature of the fallout from the financial crisis. Regarding timing, only one bank, the German IKB, was rescued before the first concerted liquidity provision by global central banks on August 8, 2007. The last bailouts in the sample are recorded on April 2, 2010 whereas events have been collected systematically for this sample until March 10, 2011. As mentioned earlier, we collapse the data into just two periods, pre- and post August 8, 2007, to test whether the cross-sectional difference in implied connectivity measures correlates with an assigned SIFI status of banks as revealed by bailouts.

Centrality and other SIFI determinants

In order to validate the measures of degree and Bonacich connectivity for financial institutions we evaluate their relation with future bailouts. To this end we estimate a simple logit model with the dependent variable equal to one if a financial firm was bailed out and zero otherwise. The first announcement of a rescue measure constitutes the event. In case of successive rescue measures during the sample period, we denote these as one event. To avoid endogeneity, we predict bailouts *during* the crisis with indicators of connectivity based on co-crash probabilities pertaining to the *pre-crisis* period. If this measure of inferred connectivity is informative, we hypothesise that policy makers are more inclined to bail out banks they considered connected already prior to the crisis, i.e. identified as SIFI.

We measure connectivity by direct degree centrality and in a gatekeeper sense using Bonaccic centrality. Both measures are calculated on the basis of both equity return and CDS spread change series. The descriptive statistics for these variables are shown in Table 2.7.

Table 2.7. **Descriptive statistics of bailout determinants: centrality indicators and firm-specific factors**

Variables	Values in	Mean	SD	Obs.	Min	P25	P50	P75	Max
CDS centrality									
Degree	(%)	68.97	21.99	186	9.19	60.54	75.68	84.86	99.46
Bonacich	(%)	40.61	22.38	186	0.00	23.24	37.38	56.22	99.43
Equity centrality									
Degree	(%)	20.03	13.60	164	0.61	8.59	16.56	30.06	53.37
Bonacich	(%)	41.78	20.36	164	0.00	27.46	38.89	57.12	98.46
Rescue measures									
Capital injections	(B USD)	12.43	17.69	50	0.53	2.84	5.02	18.2	88.62
Asset guarantees	(B USD)	50.91	78.44	21	0.26	6.33	15.12	41.15	283
Control variables									
Total Assets	(B USD)	328.62	499.35	138	0.02	20.91	104.77	337.49	2,070.02
CCP with market	(bp)	21.39	3.85	164	7.89	19.50	21.49	23.91	31.42
CAPM Beta		0.26	0.16	164	-0.09	0.14	0.25	0.33	1.01
Solvency ratio	(%)	15.54	19.07	138	1.25	4.75	6.88	18.12	99.14
RoA	(%)	2.04	4.79	138	-27.59	0.86	1.43	2.48	22.10

Notes: Centrality measures are reported in percentages. Degree centrality reflects the proportion of members with which the institution shares a significant co-crash probability, i.e. a co-crash probability for which the null of unit tail index could not be rejected at the one-percent significance level. The Bonacich centrality measures are rescaled to percentages where zero percent indicates that the institution is not connected to institutions that do not share a significant co-crash probability but are highly connected with other members; higher values indicate that the institution acts as a gatekeeper in the sense of sharing a significant co-crash probability with multiple independent institutions which are themselves highly connected with others. All variables cover the period January 2004 through August 2007, except for Total Assets (book value), Solvency ratio and RoA, which are obtained for the fiscal year of 2006 only.

The data shows that the network in terms of direct credit risk connections is more densely connected compared to equity ties. For the average financial institution, we could not reject the dependence assumption in terms of extreme co-movements of CDS spread change series for 69% of all possible connections. For equity return co-movements, this share is only 20% on average, indicating that the average financial institution is only significantly tied to one out of five potential peers via extreme joint equity return spikes.

We also show in Table 2.7 mean values for the gatekeeper type of centrality, the Bonacich indicator. These are scaled in such a way that larger percentages indicate a more central role in the network in terms of connecting more clusters of other financial institutions in the network. This indicator yields virtually identical averaged “gatekeeper” importance for both CDS and equity based connectivity.

As noted in BIS (2013), the SIFI status of financial institutions should also reflect additional factors other than connectivity. Among the most important ones are too-big-to-fail concerns. To this end we augment our analysis with a set of control variables that stem from the period before the Global Financial Crisis period, and in particular cover the period January 2004 through August 2007 unless stated otherwise. We specify the log of total assets,[14] using total assets from the fiscal year of 2006. Additionally, bailout choices may have been driven by concerns of systemic importance that a specific failure would lead the entire system to collapse. The notion of systemic importance that emphasizes the relationship between individual institutions and the entire market is central to recent measures, such as marginal expected shortfall (Acharya et al., 2012) and $\Delta CoVaR$ (Adrian and Brunnermeier, 2011). We specify here also an EVT-based measure, namely the co-crash probability of each institution with the market as in (De Jonghe, 2010). This variable CCP market thus estimates for each financial firm the probability that it's stock prices crashes jointly with the entire financial market index.[15] We employ the method outlined above in Section 2.3 to estimate this variable.

Finally, we control for the idiosyncratic risk-return traits of each financial firm. These are likely to co-determine the choice of regulators regarding bailouts as well.[16] Specifically, we specify CAPM betas, solvency ratios, and return on assets (RoA), which we obtain from Datastream. The solvency ratios and RoA are obtained from the fiscal year of 2006 only.

Too-connected-to-fail: Which type of network centrality matters?

Table 2.8 shows below the marginal effects from logit estimations to test the too-connected-to-fail notion based on degree centrality for equity (columns 1–4) and CDS ties (columns 5–8), respectively. Results in columns (1) and (5)

[14] Specification of total employees as a robustness check did not qualitatively change the results.

[15] We only specify an equity market CCP because for CDS no reliable index is available.

[16] For example Duchin and Sosyura (2014) discuss that equity capital support to U.S. banks was granted on the basis of an assessment of the future viability of the bank, implying for example an assessment of profitability and liquidity outlooks.

show that an increase of 1% in the proportion of significant ties over all possible ties that a financial firm has with its sampled peers leads to an increase in the probability of receiving bailout support during the crisis in the order of 5.4%. This result suggest that financial institutions that are more central in terms of sharing significant extreme CDS spread return co-movements with peers are both statistically and economically more likely to be considered worthy of a bailout. Further support for this finding is obtained from the are under the ROC curve, or the coefficient of concordance, which for column (5) is significantly larger than the benchmark value obtained for the baseline logit regression in which no connectivity variables are included. Hence, the discriminatory power of the model increases when including CDS-spread based connectivity measures.

Table 2.8. **Rescue measures explained by pre-crisis degree centrality**

Received gov. support during the crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equity degree centrality, in logs								
Overall	0.071							
	[0.050]							
Intra-industry		0.048						
		[0.044]						
Intra-country			-0.013					
			[0.016]					
Intra-country/industry				0.009				
				[0.017]				
CDS degree centrality, in logs								
Overall					0.054***			
					[0.018]			
Intra-industry						0.051***		
						[0.019]		
Intra-country							0.046***	
							[0.017]	
Intra-country/industry								0.038**
								[0.017]
Controls								
ln(Total Assets)	0.093***	0.100***	0.103***	0.097***	0.106***	0.107***	0.107***	0.109***
	[0.023]	[0.021]	[0.019]	[0.021]	[0.026]	[0.027]	[0.025]	[0.026]
Co-crash probability	-0.009	-0.009	-0.007	-0.006	-0.001	-0.001	-0.001	-0.001
with market index	[0.009]	[0.009]	[0.008]	[0.008]	[0.009]	[0.010]	[0.009]	[0.010]
CAPM Beta	-0.178	-0.151	-0.113	-0.065	-0.087	-0.094	-0.090	-0.090
	[0.224]	[0.233]	[0.209]	[0.225]	[0.171]	[0.185]	[0.180]	[0.195]
Solvency ratio	-0.032**	-0.033**	-0.034**	-0.031**	-0.029	-0.030	-0.033	-0.034
	[0.014]	[0.014]	[0.015]	[0.015]	[0.023]	[0.024]	[0.023]	[0.024]
RoA	0.042**	0.045**	0.048**	0.044**	0.039	0.040	0.044	0.048
	[0.020]	[0.021]	[0.021]	[0.022]	[0.032]	[0.035]	[0.032]	[0.035]
Observations	124	124	124	124	112	112	112	112
log-likelihood	-50.712	-51.489	-51.850	-51.938	-38.375	-38.645	-39.720	-40.623
Pseudo R^2	0.261	0.250	0.244	0.243	0.410	0.406	0.390	0.376
Area under ROC curve	0.838	0.832	0.826	0.825	0.904**	0.902*	0.892	0.888

Notes: Table reports the marginal effect of variables derived from logit regressions for whether an institution received financial support or guarantees from central regulators during the Global Financial Crisis. The regressors are obtained in the pre-crisis period. Bootstrap standard errors are reported in brackets, 1000 replications. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level. 'Area under ROC curve' reports the coefficient of concordance and whether it differs significantly relative to the value obtained where degree centrality measures are excluded.

In columns (2) – (4) and (6) – (8) we show results for degree centrality calculated for three different sub-samples. Intra-industry degree centrality relates the significant co-crash probabilities per financial institutions not to all possible ties, as in the baseline, but only to those possible connections within the firm's own financial sector. For example, we relate bank connections only to all possible connections with other banks, but exclude insurances, investment funds, and so forth. Likewise, intra-country connectivity confines the set of possible connections only to financial firms within a country. The last, and smallest possible connectivity set is the one confined by both industry and country, say only banks in the US are considered possible connectors. These alternatives gauge whether the role of connectivity to predict policy makers' choices to bailout banks increasing in increasingly narrow definitions of potential peers. A potential reason for such a pattern is the fact that, for example, explicit rescue schemes were usually orchestrated and targeted at specific sector of the financial industry in a single country, such as equity support to banks under the Capital Purchase Program as part of TARP in the US or the direct equity support of German banks by the Financial Market Stability Authority. The evidence in Table 2.8 suggests that centrality in increasingly narrowly defined networks prior to the financial crisis bears little or no explanatory power of bailouts after August 7, 2007. Although the coefficients in of the CDS-based centrality measures in columns (6) – (8) are significantly different from zero, the model's discriminatory power is not significantly better relative to the benchmark model with no centrality measures specified.

Overall, there is statistical evidence of too-connected-to-fail considerations based on pre-crisis degree centrality for bailout choices during the crisis. A comparison with the other control variables vividly illustrates that the too-big-to-fail consideration used to be the major driver of bailout probabilities. An increase in financial firm size as measured by the log-level of total assets by 1% increased the bailout probability by 9% – 10%. This result corroborates regulators' emphasis on identifying SIFIs in particular in terms of size.

Table 2.9. **Rescue measures explained by pre-crisis Bonacich centrality**

Received gov. support during the crisis	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equity Bonacich centrality in logs								
Overall	0.199**							
	[0.089]							
Intra-industry		0.131***						
		[0.038]						
Intra-country			0.073***					
			[0.024]					
Intra-country/industry				0.131***				
				[0.047]				
CDS Boncacich centrality in logs								
Overall					0.101***			
					[0.035]			
Intra-industry						0.151***		
						[0.052]		
Intra-country							0.043	
							[0.029]	
Intra-country/industry								0.086*
								[0.048]
Controls								
ln(Total Assets)	0.087***	0.048*	0.098***	0.077***	0.103***	0.086***	0.111***	0.102***
	[0.022]	[0.029]	[0.020]	[0.020]	[0.025]	[0.026]	[0.026]	[0.026]
Co-crash probability	-0.016	-0.010*	-0.001	0.003	-0.001	0.003	-0.000	0.002
with market index	[0.010]	[0.006]	[0.010]	[0.012]	[0.008]	[0.012]	[0.010]	[0.012]
CAPM Beta	-0.198	-0.135	0.051	0.124	-0.088	0.034	-0.120	-0.044
	[0.205]	[0.140]	[0.218]	[0.237]	[0.179]	[0.214]	[0.196]	[0.222]
Solvency ratio	-0.034**	-0.019*	-0.028*	-0.021	-0.032	-0.024	-0.043**	-0.039
	[0.014]	[0.010]	[0.015]	[0.015]	[0.022]	[0.024]	[0.021]	[0.024]
RoA	0.043**	0.037**	0.035	0.024	0.042	0.037	0.058*	0.052
	[0.020]	[0.016]	[0.022]	[0.022]	[0.031]	[0.036]	[0.030]	[0.036]
Observations	124	124	124	124	112	112	112	112
log-likelihood	-49.269	-45.036	-48.854	-45.500	-39.305	-34.324	-42.926	-41.201
Pseudo R^2	0.282	0.344	0.288	0.337	0.396	0.473	0.340	0.367
Area under ROC	0.852	0.879	0.841	0.862	0.926**	0.897	0.872	0.887

Notes: Table reports the marginal effect of variables derived from logit regressions for whether an institution received financial support or guarantees from central regulators during the Global Financial Crisis. The regressors are obtained in the pre-crisis period. Bootstrap standard errors are reported in brackets, 1000 replications. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level. 'Area under ROC curve' reports the coefficient of concordance and whether it differs significantly relative to the value obtained where Bonacich centrality measures are excluded.

In Table 2.9 we replace the degree centrality measures with the Bonacich centrality measures. As before, for columns (1) – (4) and (5) – (6) we specify respectively equity-based Bonacich centrality and CDS-based centrality. In columns (1) and (5) we find that both equity-based and CDS-based pre-crisis Bonacich centrality pertains positively and statistically significant to our rescue measure. In the case of column (5), this indicates that if the number of times an institution acts as a key link that connects two institutions along the shortest path by 1% a bailout is more likely to be received in the order of 10.1%. What's noteworthy about the specification in column (5) is the discriminatory power of the specification. The significance of the area under the ROC curve indicates that CDS-based Bonacich centrality marks an economically relevant addition to the baseline specification.

In columns (2) – (4) and (6) – (8) we specify Bonacich centrality measures in addition to the controls for which we consider network ties within industries, within countries, and within both industries and countries as in 2.8. For instance, for the intra-industry equity-based Bonacich centrality measure we restrict ties that are interindustry to zero, such that the possible shortest paths along which firms are connected can only be of an intra-industry nature. Throughout we find positive and statistically significant results except for columns (7) and (8). However, as in the case of column (1) the Area under ROC curve does not significantly improve upon the baseline value. Hence, the restricted types of centrality do not significantly contribute to the discriminatory power of the model.

Table 2.10. **Centrality and the nature of ties**

Received gov. support during the crisis			
	(1)	(2)	(3)
Degree centrality in logs			
Equity based	0.066		-0.069
	[0.045]		[0.088]
CDS based	0.017		0.028
	[0.017]		[0.044]
Bonacich centrality in logs			
Equity based		0.019	-0.035
		[0.033]	[0.085]
CDS based		0.192**	0.304**
		[0.091]	[0.152]
Controls			
ln(Total Assets)	0.100***	0.088***	0.086***
	[0.027]	[0.027]	[0.030]
Co-crash probability	-0.005	-0.012	-0.018
with market index	[0.011]	[0.011]	[0.012]
CAPM Beta	0.159	0.087	0.176
	[0.275]	[0.257]	[0.248]
Solvency ratio	-0.045	-0.050*	-0.057**
	[0.028]	[0.026]	[0.028]
RoA	0.056	0.062*	0.074*
	[0.040]	[0.037]	[0.039]
Observations	78	78	78
log-likelihood	-34.526	-32.293	-30.056
Pseudo R^2	0.450	0.486	0.522
Area under ROC	0.913	0.923*	0.944***

Notes: Table reports the marginal effect of variables derived from logit regressions for whether an institution received financial support or guarantees from central regulators during the Global Financial Crisis. The variables are obtained in the pre-crisis period. Bootstrap standard errors are reported in brackets, 1000 replications. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level. 'Area under ROC curve' reports the coefficient of concordance and whether it differs significantly relative to the value obtained where degree and Bonacich centrality measures are excluded.

In Table 2.10 we present the results associated with the joint specification of degree and Bonacich centrality for the cases when they are both equity and CDS based. Results further corroborate the previous findings presented in Tables 2.8 and2.9. CDS based Bonacich centrality pertains significantly to our rescue measure. Based on columns (2) and (3) we find that a 1% increase in CDS based Bonacich centrality increases the probability of receiving financial support from central regulators respectively by 20% and 30% points. Upon evaluating the coefficient of concordance for columns (2) and (3) we find that the specification of Bonacich centrality measures results in a improvement of the model's discriminatory powers in distinguishing between whether an institution received support. This result indicates that regulators incorporated the centrality of financial institutions in their decision to extend bailout supper during the Global Financial Crisis, and paid in particular attention to those institutions that are central in the gatekeeper sense of connecting highly connected hubs of financial institutions. At the same time, the logarithm of total assets stands out as a variable that pertains positively to the probability of receiving bailout support with an effect of 9% point as a result of a 1% increase in total assets. Additionally, the solvency ratio shows a detrimental effect on the probability of receiving bailout support, indicating that firms with higher leverage where more likely to receive bailout support during the crisis period.

Table 2.11. **Centrality and the intensity of rescue measures**

Dependent variable	Capital injections ($B)			Asset guarantees ($B)		
	(1)	(2)	(3)	(4)	(5)	(6)
Degree centrality in logs						
Equity based	-3.093		-17.750*	38.162		62.468
	[4.909]		[9.665]	[24.944]		[44.770]
CDS based	4.973**		-5.557	8.645		-3.708
	[1.955]		[5.493]	[7.420]		[18.022]
Bonacich centrality in logs						
Equity based		2.907	33.345*		46.214	-47.436
		[8.835]	[19.488]		[36.869]	[70.604]
CDS based		10.166**	19.979**		18.425	24.637
		[3.876]	[10.051]		[15.103]	[36.126]
ln(Total Assets)	13.663***	12.749***	11.212***	32.651**	30.336**	32.491**
	[3.388]	[3.491]	[2.640]	[13.297]	[12.968]	[13.755]
Co-crash probability	-1.088	-1.152	-1.922	3.823	2.661	5.728
with market index	[1.073]	[1.117]	[1.183]	[4.453]	[4.332]	[5.038]
CAPM Beta	-28.301	-35.257	-20.109	-57.102	-16.929	-59.551
	[24.006]	[26.790]	[20.818]	[95.126]	[90.549]	[96.291]
Solvency ratio	-2.706	-2.431	-3.773*	0.065	-1.489	0.898
	[2.057]	[1.996]	[2.001]	[5.160]	[5.780]	[4.405]
RoA	3.780	3.210	5.305*	0.573	2.648	-0.217
	[2.894]	[2.802]	[2.781]	[8.639]	[9.396]	[8.012]
Constant	-29.441	-38.581	-11.872	-458.201**	-398.178*	-479.144**
	[31.343]	[30.794]	[29.334]	[222.369]	[204.394]	[220.547]
Observations	78	78	78	78	78	78
lnL	-139.131	-138.521	-136.003	-78.789	-79.704	-78.254
pseudo-R-squared	0.180	0.184	0.199	0.155	0.145	0.161

Notes: Table reports parameter coefficient estimates associated with variables included inTobit regressions for whether and to what extend, in U.S. dollars, an institution received positive capital injections, (1) – (3), or positive asset guarantees, (4) – (6), from central regulators during the Global Financial Crisis. The variables are obtained in the pre-crisis period. Bootstrap standard errors are reported in brackets, 1000 replications. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level.

In Table 2.11 we explore in a series of six Tobit regressions whether and to what extend centrality contributed to the intensity of the bailout support extended by central regulators during the Global Financial Crisis. We distinguish between two types of rescue events: capital injections, columns (1) – (3), and asset guarantees, columns (4) – (6). For those firms that received support we observe the amount they received or the asset value guaranteed and regard the values for institutions that did not receive bailout support as missing such that the data is left censored at zero. For the case of capital injections we find that an increase of 1% in Bonacich centrality results in a $10.17B and $19.98B increase in capital injections during the crisis. We can not claim that capital injections were indeed effective in preventing institutions from collapsing, because we lack the counterfactual. However, since this result is obtained while controlling for size, it indicates that central regulators were not solely concerned with the institutions' 'sizes' but also incorporated connectivity in their decision to extend bailout support. We do not find this result for the case in which the regulator extended asset guarantees. These guarantees seem to be primary driven by the institution's size in the form of total assets. Results also suggest that asset guarantees are more sensitive to changes in total assets relative to capital injections. In columns (4) – (6) we report a marginal effect of about $31.00B change in extended asset guarantees as a result of a 1% increase in total assets.

2.5 Conclusion

We employ Extreme Value Theory to measure tail risks of financial firms and use the proposed method to assess interconnectedness between these firms. Based on a comprehensive sample of daily CDS spreads for 186 financial firms, and daily stock prices for 164 institutions we calculate a so-called co-crash probability (CCP) for all possible pairs of these financial firms. We use return rates on credit default swap quotes and stock prices between January 2004 and August 2007 and employ a bootstrap method to obtain standard errors of potential CCP ties to assess the statistical significance of our joint crash probability estimates. The main results are as follows.

Although it is not necessarily borne out by our method, we find CCPs to be larger across percentiles if we fail to reject asymptotic dependence between the underlying series. This finding indicates that for institutions for which we gather evidence of dependence in their performance under extreme conditions we also find that the probability that both institutions face a detrimental decline in their performance is generally estimated to be higher as well. Exactly how performance in this respect is affected depends on for instance direct credit events where one firm affects the credit position of the other; indirect events stemming from third parties which affect both institutions in question jointly; or changes in the market's perception of long term profitability prospects. To avoid the trap of interpreting our CCP measure in an ad hoc manner as a measure of interconnectedness we employ tests to validate the economic significance of the CCP along the lines of the *too-connected-to-fail* hypothesis.

To this end we use the CCP estimates and the test results for dependence between the CCP's underlying series to identify those institutions that take central positions in the financial sector. From the CCP estimates we infer two types of centrality: degree centrality and Bonacich centrality. The former measures an institution's centrality as the proportion of other institutions with which the institution in question shares dependence in extreme returns in either CDS spreads or share prices. The latter, Bonacich centrality, measures the total number of times an institution connects two other institutions along the shortest path, for which a CCP estimate with a high value denotes a small distance. Whereas degree centrality has the potential to capture direct contagion between any two firms, Bonacich centrality can reveal whether an institution is central in a 'gatekeeper' sense by connecting hubs of highly connected peers. By estimating the relation between the network measures and rescue measures implemented by central regulators during the Global Financial Crisis we aim to validate the CCP estimate as a measure of interconnectedness.

Results indicate that the CDS-based Bonacich centrality measure pertains positively to the likelihood of receiving capital injections and asset guarantees implemented by central regulators during the Global Financial Crisis. This result is indicative that central regulators are not primarily concerned with the institution's size in terms of total assets, leverage, and other idiosyncratic risk factors, but also focus in particular on whether an institution is central in the financial sector in the gatekeeper's sense. A similar result is found for the relation between CDS-based Bonacich centrality and the magnitude of the capital injections implemented during the Global Financial Crisis. Here we find that if an institution experiences a one percent increase in the total number of times the institutions connects along the shortest path via the estimated CCP network it is likely to have received a 20B USD worth of capital injections. Asset guarantees on the other hand are primarily explained by past levels of total assets.

2.A Appended tables

Table 2.A.1. **Countries within regions**

U.S.	Europe	O.D.	E.M.
United States (US)	Austria (AT)	Australia (AU)	Argentina (AR)
	Belgium (BE)	Canada (CA)	Brazil (BR)
	Denmark (DK)	Hong Kong (HK)	China (CN)
	France (FR)	Japan (JP)	India (IN)
	Germany (DE)	Singapore (SG)	Indonesia (ID)
	Greece (GR)		Kazakhstan (KZ)
	Iceland (IS)		Korea (KR)
	Ireland (IE)		Malaysia (MY)
	Italy (IT)		Russia (RU)
	Luxembourg (LU)		South Africa (ZA)
	Netherlands (NL)		Taiwan (TW)
	Norway (NO)		Thailand (TH)
	Portugal (PT)		Turkey (TR)
	Spain (ES)		Ukraine (UA)
	Sweden (SE)		
	Switzerland (CH)		
	United Kingdom (GB)		

Notes: ISO 3166 country codes reported in parentheses. In the classification of "Other Developed" and "Emerging Markets" we follow the MSCI country classification.

Chapter 3

Executive Compensation and Systemic Risk Formation

3.1 Introduction

In light of the substantial cost of the financial crisis of 2007/2008, higher compensation in the financial industry compared to other sectors of the economy (Kaplan and Rauh, 2010), and in particular that of top bankers at failed institutions (Bebchuk et al., 2010), fuelled public fury. Diamond and Rajan (2009) conjectured that bank executives' compensation schemes, inability to assess tail risks of novel financial products, and lack of control over other executives' actions were important factors that contributed to the near-collapse of the financial system. Aside from conventional (idiosyncratic and systematic) risk, the contribution of individual institutions to the risk that the entire system fails appears to be the main motive for concerns about executive compensation in contemporary policy making. We test the relationship between past bank executive compensation and *systemic* risk formation during the crisis, explicitly gauging the tail nature of systemic risk.

We investigate the relationship between 92 U.S. banks' executive pay

This chapter is based on joint work with Michael Koetter.

components in 2006 and five systemic risk indicators that cover the period July 2007 through December 2008.[1] We specify executive compensation *prior* to the crisis to explain systemic risk per institution during the crisis to avoid endogeneity by construction. Our focus is thus on cross-sectional differences of risk cultures across U.S. banks that are emphasized in Cheng et al. (2010) and Fahlenbrach et al. (2012).[2]

Most studies focus on CEO compensation, which may be unable to monitor (too) large and complex banks effectively (Diamond and Rajan, 2009). Kim et al. (2011) show indeed that it is the option portfolio value of Chief Financial Officers (CFOs), not CEOs, which correlates with dramatic stock price slumps, thereby corroborating the importance of non-CEO compensation. Therefore, we test for the existence of a relationship between systemic risk, CEOs, *and* non-CEOs compensation schemes.

The swift policy responses to regulate bank executive pay in the U.S. and elsewhere is without precedent[3], and remarkable because of the scant evidence that bankers pay prior to the crisis correlated with risk and performance during the crisis. Whereas some studies investigate the effects of bank manager incentives and compensation on risk and performance, the evidence is mostly confined to samples before 2006.[4] The systemic turmoil

[1] We consider two variants of systemic capital shortfall (Acharya et al., 2012; Brownlees and Engle, 2012), $\Delta CoVaR$ (Adrian and Brunnermeier, 2011), co-crash probabilities of individual banks with the equity market based on extreme value theory (Hartmann et al., 2004b; De Jonghe, 2010), and a simple Troubled Asset Relief Program (TARP) recipient indicator (Duchin and Sosyura, 2012,0).

[2] See also Henri (2006) on the influence of organizational culture differences and performance measurement in non-financial firms.

[3] The U.S. Treasury installed binding compensation guidelines for all banks using TARP, endorsed by Secretary Geitner, Federal Reserve Chairman Bernanke, and President Obama.

[4] Chen et al. (2006) contradict early evidence by Houston and James (1995) by showing for a sample of 591 U.S. bank CEO-years between 1992 and 2000 that bank executives were increasingly compensated in stock-options after deregulation. Subsequently, various market risk measures derived from a CAPM model augmented with interest rates increased. Chesney et al. (2012) emphasize the difference between equity and asset incentives of (bank) executive pay. Only the latter considers leverage of the banking firm, which is central to the theoretical prediction that owners and managers incentives are aligned at the expense of debt holders. They show for a sample of U.S. financial institutions' CEOs between 2003 and 2006 that asset incentives, measured as vega and delta, increased risk measured in terms of loan write-downs. These metrics denote the dollar response in CEO stock and cumulative stock option wealth in response to a 1% change in *asset* return volatility (vega) and

in financial markets is illustrated best by the first concerted action of various central banks to provide liquidity on August 7, 2007.

An important exception is Fahlenbrach and Stulz (2011), who show that high-powered incentives of bank CEOs prior to the crisis did not lead to worse bank performance during the crisis. They provide some evidence that larger equity-based pay of 92 U.S. bank CEOs in 2006 did explain worse performance during the crisis, measured in terms of buy-and-hold returns, return on equity (RoE), and return on assets (RoA) between July 2007 and December 2008. However, they do not find any correlation for option and cash components of pay and performance. Based on the result that CEOs did not shed stocks during the crisis period, some argue that high-powered incentives of senior management did not lead to excessive risk taking.[5] Acrey et al. (2011) consider bank risk more explicitly. They regress compensation components of 84 U.S. bank CEOs in 2006 on variables used by prudential supervisors to assess banks' stability with so-called CAMEL ratings as well as expected default frequencies calculated from market data in 2008. Their results confirm Fahlenbrach and Stulz (2011) to the extent that they find no relationship between option and cash compensation components with any of these risk measures.

A possible explanation is that these studies consider idiosyncratic or systematic risk during the crisis. However, the concerns reflected by policy actions and the public pertain to large and important banks that exploit opportunities associated with *systemic* risk, which is particular to the banking industry. John et al. (2000) show that neglecting managerial compensation in the pricing of deposit insurance *ex ante* leads owners and managers to excessive risk taking, which is shifted ultimately to tax payers. Freixas and Rochet (2013) emphasize that the failure of depositors to monitor their bank is in particular aggravated for systemically important financial institutions,

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firm value (delta). Conventionally used *equity* incentives based on stock return volatility and stock prices explain little risk-taking among financial institutions. DeYoung et al. (2013) find that between 1994 and 2006, CEOs of U.S. commercial banks with high (equity) vega took more risk measured in terms of riskier loan portfolios, larger fee-based income sources, and more securitization activity.

[5] A view criticized vocally by Bebchuk et al. (2010).

which enjoy in addition to deposit insurance an implicit too-important-to-fail guarantee. Such implicit insurances therefore generate incentives for owners and incentive-aligned managers compensated in stocks and options to exploit this externality in the form of loading systemic risk.

Our results show in line with Fahlenbrach and Stulz (2011) that managerial compensation traits prior to the crisis have no significant impact on idiosyncratic bank profitability, equity returns, and return volatility during the crisis. Likewise, cash bonuses, managerial ownership, and equity portfolio risk sensitivity of CEOs have no effect on most systemic risk measures. However in line with the concerns raised by John et al. (2000), Diamond and Rajan (2009), and Freixas and Rochet (2013), we find that higher cash bonuses of non-CEO executives increase all but one indicator of systemic risk taking significantly. The consideration of bank executive pay beyond the CEO therefore seems crucial in potential future regulation. These effects are driven by a subset of banks, which are systemically most important as measured by their contribution to aggregate capital shortfall of the entire system.[6] Analyzing compensation components separately, we find that selected classical solutions to the agency problems between owners, managers, and shareholders can be effective. Selected long-term incentives for non-CEOs reduce systemic risk, namely larger stock option shares and deferred earnings. Controlling for differences in corporate governance, imprinting conditions reflected by the tenure of executives, and compensation gaps between CEOs and non-CEOs does not alter these results.

This Chapter is organized as follows. We discuss executives' incentives and the sample of U.S. financial institutions in Section 3.2 before presenting the methodologies to measure systemic risk in Section 3.3. We discuss results in Section 3.4 and conclude in Section 3.5.

[6] Bank of America, Citigroup, Goldman Sachs and Morgan Stanley.

3.2 Incentives, hypotheses, and data

3.2.1 Incentives and hypotheses

For non-financial firms, the two canonical agency conflicts are between shareholders and managers and between shareholders and debt holders. The seminal paper by Jensen and Murphy (1990) shows that the former is resolved if managers' incentives are tied through incentive compensation to the development of shareholder wealth, for instance by means of stock payments, or 'skin in the game'.[7]

But the alignment of incentives pertaining to the first agency problem can amplify the latter conflict between shareholders and debt holders. Under limited liability, managers now share the risk-shifting incentives of equity owners to depositors. This problem is particularly relevant in the presence of deposit insurance, which eliminates the incentives of depositors to monitor risk taking by manager-owners.

Deposit insurance thus represents an externality that shareholders and incentive-aligned managers can exploit if the insurance premium is ill-designed. In light of the Savings and Loans crisis in the U.S., John et al. (2000) showed that the socially optimal premium of deposit insurance should depend *ex ante* on management compensation to avoid excessive risk taking.[8] Note that it is sufficient for the optimal contract to state the equity and option component rather than having to impose a certain cap on either the level or the composition of compensation. Since 2007, the Federal Deposit Insurance Corporation (FDIC) calculates risk-based premiums for U.S. banks that are

[7] If stock markets are efficient, managers have an incentive to maximize long-term performance of the firm when compensated in stocks (Murphy, 1999). Because stock prices incorporate all information about banks' long term performance, a short-term focus reduces management's wealth due to resulting lower stock prices. However, Jensen (2004) finds that the overvaluation of equity in inefficient markets leads to misaligned incentives for management to pursue shareholders' interests. Thus, contracts in which managerial incentives are seemingly aligned with shareholders' interests are no guarantee for shareholder wealth maximizing choices by the management.

[8] John et al. (2010) provide empirical evidence that it can be optimal for shareholders to induce their management to engage in risk-shifting activities in order to increase the 'put' value of the deposit insurance provided by the FDIC.

covered by the Deposit Insurance Fund (DIF).

However, Freixas and Rochet (2013) develop a model where the bank in question is too large to unwind. For such a systemically important financial institution (SIFI), they show that shareholders will always have an incentive to remunerate (new) managers with high performance bonuses, which will lead to excessive risk taking. Such systemic risk charges are not part of contemporaneous prudential regulation. Accordingly, they argue for even tighter regulation in the hand of a central planner, a so-called Systemic Risk Authority (SRA), which can limit bank executives' pay and restructure the SIFI, i.e. expropriate owners and replace managers. Neither deposit insurance nor capital charges accounted (yet) for systemic risk nor did a SRA exist with a far-reaching mandate during the financial crisis of 2007/2008.

Therefore, we hypothesize that the relation between larger ownership shares of executives and higher equity-based compensation components with systemic risk is positive. Alternatively, the possibility of losing the charter because of failure became a real one after the Lehman collapse. *Ex ante*, bank managers and owners that were uncertain about whether they qualified as a SIFI might have been effectively disciplined by classical equity incentives. Second, Bolton et al. (2006) show that managers may assign more weight to the short-term performance of stock prices so as to benefit from speculative behavior in the stock market. Therefore, we expect that short-term performance pay spur systemic risk taking. We follow Fahlenbrach and Stulz (2011) and measure short-term performance pay by cash bonuses.

However, the prospect of receiving bailout support by SIFI institutions and its potential to induce moral hazard in risk-taking behavior by management may not be the full story to explain systemic risk formation. Issues of internal bank governance and heterogeneity in incentives of managers at various levels along the hierarchy within a bank may also affect the bank's risk position. Boot and Schmeits (2000) study the optimality of conglomeration and argue that the benefit of coinsurance for divisions in a conglomerate induces management to no longer fully internalize their risk-taking behavior. This change in behavior by division management can aggregate to excessive risk taking at the overall firm level. Esarey (2011) argues that it is difficult for senior management to implement in bureaucratic institutions adequate contracts that solve internal principal-agent problems among divisions' management. In order to motivate managers to perform in such organizations competitive procedures over budget allocation are considered by Esarey (2011).

In this light compensation of management is often tied to the performance of the division, department or business unit; in particular when it comes to bonuses and equity-based compensation. The scope of the aforementioned internal principal-agent problems is likely to depend on the relative size of compensation tied to the manager's performance and the extent with which the CEO is concerned with internalizing the default risk of the firm. If the CEO only partially internalizes the risk of default as a result of future bailout prospects, there can be scope for division managers to not fully internalize their risk-taking behavior. This situation has the potential to agravate the problems associated with lack of internal bank governance and can lead to additional systemic risk formation driven by divisions' management taking inefficient project as a result of coinsurance among divisions, or competition for a larger slice of the budget. This motivates us to include non-CEO executives' compensation schemes in the analysis in addition to the CEO's.

3.2.2 Executive compensation data

To investigate if CEO and non-CEO compensation from before the crisis contributed to systemic risk during the period between July 2007 through December 2008, we closely follow Fahlenbrach and Stulz (2011) to construct our sample and compensation proxies.[9] Although the crisis did not end by 2008, the period includes the substantial decline in banks' stock prices, the uncertainty about the stability of the whole system, and the responses of central banks. Given the widespread bailout and governmental support

[9] We derive systemic risk measures in Section 3.3 using market value data of financial firm equity and the total return index of stocks from Thomson Reuter's Datastream from 1992 to 2011.

schemes to stabilize the financial system after 2008, we limit our sample period until then.

We select financial firms with a Standard Industry Classification (SIC) code between 6000 and 6300, which yields 92 unique financial firms available for analysis.[10] We gather bank balance sheet data from the Orbis database of Bureau Van Dijk. Table 3.1 reports summary statistics on these financial accounts data.

[10] We exclude SIC code 6292 because these firms are engaged solely in investment advice.

Table 3.1. **Descriptive statistics on balance and income sheet data**

variable	**mean**	**sd**	**N**	**p25**	**p50**	**p75**
Values in millions of USD						
Revenue	4,971.2	14,547.7	92	130.2	493.7	1,627.0
Gross income	1,637.1	5,140.4	92	33.3	149.5	460.6
Net Income	1,164.9	3,557.1	92	26.9	129.1	461.2
Cash Flow	40.8	32.8	78	25.2	38.5	110.5
Total Assets	91,473.8	301,405.5	92	1,885.0	6,081.5	17,899.9
Shareholder Funds	7,448.4	21,891.6	92	344.4	1,033.4	3,852.2
Deposit and short term funding	55,345.3	201,823.4	83	845.3	1,822.2	11,252.1
Values in percentages						
Current ratio	1.0	2.9	58	0.2	0.3	0.8
Profit margin	32.1	19.0	92	20.5	32.5	44.0
Return on equity *RoE*	13.4	31.3	80	9.2	15.5	21.4
Consolidated return on equity	2.4	6.8	80	1.5	2.7	3.6
Net interest rate margin	2.2	2.3	75	1.3	2.8	3.6
Return on assets *RoA*	2.8	5.2	80	1.4	1.8	2.6
Buy & hold returns	15.31	16.89	91	4.85	14.01	24.26
Values in ratios						
Current ratio	1.0	2.9	58	0.2	0.3	0.8
Total capital ratio	6.8	6.7	80	3.1	10.8	12.3
Price earnings ratio	14.0	23.4	80	8.0	11.9	18.9
Cost to income ratio	38.0	29.1	80	25.3	50.1	63.1
Solvency ratio	21.4	19.5	80	8.3	11.5	33.2
in persons						
Number of employees	13,596.9	44,364.0	92	312.0	1,168.0	67,800.0

Notes: Table lists descriptive statistics for firm-specific variables and balance and income sheet items for the fiscal year 2006. The source of the data is Bureau van Dijk's Orbis database. The *Profit margin* is net income expressed as a percentage of revenue. *return on equity* stands for the net income as a percentage of shareholders' funds. *Net interest rate margin* is the difference between interest income and costs as a percentage of loans outstanding. *Return on assets* is net income expressed as a percentage of total assets. The *Current ratio* is defined as the quotient of current assets and current liabilities. *Total capital ratio* is defined as the sum of Tier 1 and Tier 2 capital divided by the Risk Based Assets of the bank. *Price-earnings ratio* is calculated by the quotient of the share price and the earnings per share. *Cost-to-income ratio* is the quotient of operating expenses and operating income. *RoE* is calculated by dividing the cumulative net income for the same period through total book value of equity reported for June 2007, in percentages.

In line with the Fahlenbrach and Stulz (2011) sample, the average firm is large with gross total assets of 91 billion USD and 13,597 employees on average. They are sufficiently capitalized with mean capital ratios of 6.8%, realize around 13% return on equity, and none of the banks incurred a loss in 2006.

The main variables of interest are executives' compensation components, which we obtain from the Execucomp database and which determines the size of the final dataset. Table 3.2 summarizes the compensation data for bank CEOs. Definitions of the variables presented in the table can be found in Table 3.B.1.[11]

[11] Sampled firms in Table 3.B.2 in the appendix are almost identical to Fahlenbrach and Stulz (2011).

Table 3.2. **Descriptive statistics on CEO and non-CEO compensation**

	CEO executives				*non-CEO executives*			
variable (fiscal year, otherwise 2006)	**mean**	**median**	**sd**	**N**	**mean**	**median**	**sd**	**N**
Total annual compensation								
Total compensation	6,771.3	3,191.3	8,550.5	92	3,389.4	1,310.1	6,643.3	412
Salary	716.2	745.6	267.4	92	386.4	341.8	345.2	412
Cash bonus	945.4	275.3	2,872.4	92	751.9	257.1	3,075.8	412
Non-equity incentives	1,072.3	345.3	1,940.7	92	423.3	78.8	894.6	412
Value of stock grant	1,930.1	339.2	3,939.0	88	758.3	525.9	1,621.2	403
Value of option grant	1,192.0	462.5	3,036.8	88	354.9	240.3	718.8	403
Total deferred earnings	660.8	146.0	2,762.9	79	172.6	0.0	645.4	368
Other compensation	335.1	115.0	1,274.6	92	229.6	41.8	883.4	375
Cash bonus / Salary*	1.5	0.5	6.0	92	1.6	0.7	5.7	412
Cash bonus / Salary* (2005)	2.5	1.0	6.0	91	2.1	0.8	4.2	408
Cash bonus / Salary* (2004)	1.8	1.0	2.5	83	1.8	0.8	3.1	357
Cash bonus / Salary* (2003)	2.0	0.9	4.1	77	1.6	0.7	2.9	326
Cash bonus / Salary* (2002)	1.7	0.7	3.1	66	1.5	0.7	2.9	265
Equity portfolio items								
Value of total equity portfolio	127,051.5	29,170.8	379,534.7	92	20,676.1	3,191.9	116,520.5	412
Value of shares	99,148.4	4,791.0	362,895.8	92	10,828.3	2,945.3	109,907.8	412
Value of vested shares	1,703.0	846.2	5,118.9	88	617.4	191.5	1,447.6	403
Value of exercisable options	17,809.2	4,565.1	47,476.2	85	4,897.1	1,118.8	17,386.5	395
Value of unexercisable options	1,936.0	762.4	4,040.7	85	973.2	262.6	2,431.5	395
Value of unvested restricted stock	4,475.9	783.8	11,566.1	85	2,782.4	290.6	10,303.2	403
Value of equity incentive plan	1,979.0	645.3	4,910.5	82	577.8	0.0	1,950.6	375
Value of shares / Salary*	181.3	7.2	635.6	92	18.1	8.9	202.0	412
Value of total equity portfolio / Total compensation*	53.8	7.3	187.9	82	29.5	1.8	266.2	412
Equity portfolio incentives								
Black-Scholes volatility of equity	0.2	0.2	0.1	92	0.2	0.0	0.1	412
Percentage ownership, options excluded	1.8	0.3	4.1	92	0.2	0.2	1.3	395
Percentage ownership	2.4	0.5	4.3	92	0.2	0.0	1.1	395
Percentage ownership (2005)	2.3	0.5	4.2	92				
Percentage ownership (2004)	1.4	0.4	3.8	86				
Percentage ownership (2003)	1.3	0.6	4.1	79				
Percentage ownership (2002)	1.3	0.0	3.3	68				
Board and governance								
Years in boardroom	4.6	5.0	0.9	92	3.7	5.0	1.8	412
Number of positions held during years in boardroom	0.9	1.0	0.7	92	0.8	1.0	0.7	412
Board size (in persons)	5.4	5	0.9	92				
Governance Index	10.1	10.0	2.7	78				

Notes: Table lists descriptive statistics for executive compensation for the fiscal year 2006, or for previous years stated subsequently in parentheses. All values are denoted in thousands of U.S. dollars. Items indexed with superscript "*" denote ratios. The relatively high standard deviation for Cash Bonus over Salary ratio of non-CEO executives is due to some institutions exhibiting high ratio's: Most notably Citigroup (16.1), Goldman Sachs (39.1), Morgan Stanley (27.46) and JP Morgan Chase (18.1) for the fiscal year 2006. A full description of the variables can be found in the appended Table 3.B.1.

Bank CEOs earned on average 6.8 million USD in 2006. The split across different salary components underlines the importance of variable compensation. The ratio of total cash bonuses to total fixed salaries is 1.5 on average. The wealth effect of stock and option portfolios is also large for bank CEOs. The value of shares of the bank is 180 times the value of annual fixed salaries and still a sizable factor of around 54 relative to total compensation. Equity stakes of CEOs are around 2.4% on average, reflecting substantial 'skin in the game' before the onset of the financial crisis.

The right panel in Table 3.2 shows the average values of compensation levels and composition for non-CEO board executives. The level of compensation is markedly lower at 3.4 million USD on average, but the ratio of cash bonuses compared to fixed salary components is comparable (1.6). Senior executives other than the CEO have substantially less skin in the game. Equity portfolios are just worth a multiple of 18 relative to fixed salary and 30 regarding all equity components relative to total compensation. The average stake of other senior executives is on average only 20 basis points. Non-CEOs incentives are thus much less aligned with long-term performance interests of non-management owners compared to CEOs.

3.3 Measuring systemic risk

3.3.1 Two measures of Systemic Capital Shortfall

We estimate an institution's expected capital shortfall as in Acharya et al. (2012) and Brownlees and Engle (2012) respectively. The metric gauges an insufficient capital buffer of a financial institution to meet credit obligations conditional on the entire financial system being distressed as reflected by pronounced equity market declines.

Expected capital shortfall equals the expected amount a financial institution's equity falls below a pre-specified target level of current total assets in a given period, conditional on economic downturn. This target level is denoted by k, total assets of institution i by a_i, and the future market value of equity over a horizon of p days by E_i^p. Current market value of equity is denoted by e_i and has a future random return R_i^p. We use a cumulative market return index R_m^p of the S&P 500 index to describe the state of the economy over the p day horizon. If the return of the market index falls below the critical value κ, the economy is assumed to be in an adverse state. Expected capital shortfall, CS_i^p, in a period of p days is defined as:

$$\begin{aligned} CS_i^p &:= \mathbb{E}[ka_i - E_i^p | R_m^p < \kappa] \\ &= ka_i - e_i \mathbb{E}[R_i^p | R_m^p < \kappa]. \end{aligned} \tag{3.1}$$

The current values of the threshold, total assets, and equity are observable. Therefore, we only need to estimate a conditional expectation of the future return of equity, also known as marginal expected shortfall, MES_i^p, to estimate (3.1).[12]

We follow Brownlees and Engle (2012) and Acharya et al. (2012) and set the critical threshold κ at minus twenty percent and the prudential asset ratio k at eight percent. In addition, we estimate recursively quarterly marginal expected shortfalls for institutions to match the frequency with which we observe the current values of total assets and total equity. Substitution of the estimate of marginal expected shortfall in (3.1) for $\mathbb{E}[R_i^p | R_m^p < -20\%]$ yields the expected capital shortfall estimate:

$$\widehat{CS}_{it}^p = ka_i - e_i \widehat{MES}_{i,t}^p. \tag{3.2}$$

Following the intuition of Acharya et al. (2012), an institution with a large capital shortfall is likely to trigger financial distress of others. The systemic risk measure of firm i at time t is defined as $SRISK_{it} = \max\{0, \widehat{CS}_{it}^p\}$. The relative contribution of an institution to total systemic capital shortfall is then:

$$SCS_{it} = \frac{SRISK_{it}}{\sum_{i=1}^n SRISK_{it}} \times 100. \tag{3.3}$$

SCS_{it} measures the relative weight of an institution in the formation of total systemic capital shortfall among the considered institutions and takes val-

[12] The term *marginal* reflects that for a unit increase in the equity value MES_i^p, or $\mathbb{E}[R_i^p | R_m^p < \kappa]$, denotes the change in the expected capital shortfall.

ues between 0 and 100 percent. Two types of estimates of the systemic capital shortfall are used for the purpose of our analyses: a specification based on the work of Brownlees and Engle (2012) (SCS_1) and a parsimonious specification based on Acharya et al. (2012) (SCS_2). The main difference is that the former allows for time-variant return volatilities and correlations with market returns. Dynamic volatility and correlation measures have the benefit that periods of regular market conditions and adverse conditions can be distinguished. Appendix 3.A.1 provides a complete outline of the methodologies to calculate both measures of SCS_{it}. Table 3.B.2 provides an overview of estimated values of SCS_1 for the sampled institutions. Bank of America, Citigroup, Goldman Sachs and Morgan Stanley exhibit the largest values of SCS_1, we omitted SCS_2 since it is almost identical to the reported SCS_1. This pattern is in line with the reported top ten systemically relevant financial institutions on the V-lab website of NYU Stern.[13]

3.3.2 Conditional Value at Risk of the financial sector

The third measure of systemic risk is the conditional value at risk of the financial sector at large as proposed by Adrian and Brunnermeier (2011). One of the main differences compared to the SCS_{it} measures concerns directionality. The systemic capital shortfall index is derived from the impact of the market on an institution. The conditional value at risk measure of Adrian and Brunnermeier (2011) is based on the influence of an institution on the value at risk of the market.

The so-called $CoVaR^q_{system,t|i}$ represents the value at risk of a market performance index $X_{system,t}$ conditional on the event in which the performance of an institution i, X_{it}, is about to fall short beyond a critical threshold in a particular week.[14] As threshold we use the value at risk of the insti-

[13] Based on reported values: `http://vlab.stern.nyu.edu/welcome/risk/`.

[14] We use the growth rate of the market value of total assets as bank performance measure. Market performance is measured by the average growth rate of market valued assets of all sampled institutions weighed by respective market valued total assets, see the appended Section 3.A.2 for details.

tution associated with the same threshold probability q, i.e. VaR_{it}^{q}.[15] The $CoVaR^{q}_{system,t|i}(X_{it} = VaR^{q}_{it})$ of the system is then implicitly defined by the probability of adverse market performance

$$\mathbb{P}\{X_{system,t} \leq CoVaR^{q}_{system,t|i} | X_{it} = VaR^{q}_{it}\} = q,$$

where q denotes a pre-specified quantile. We are interested in an institution's impact on the value at risk of the sector and denote the $\Delta CoVaR$ difference by

$$\begin{aligned}\Delta CoVaR^{q}_{system,t|i} :=& CoVaR^{q}_{system,t|i}(X_{it} = VaR^{q}_{i}) \\ &- CoVaR^{q}_{system,t|i}(X_{it} = median(X_{it})),\end{aligned} \tag{3.4}$$

which measures the sensitivity of the sector's value at risk to the distress of a particular financial institution i. Financial distress is defined as a departure in performance from median performance to a value at which the institution is considered to be at risk. If the value of $\Delta CoVaR^{q}_{system,t|i}$ is negligible, the market's critical value is hardly affected by the distress of institution i. A negative value indicates that the value at risk is more substantial under adverse conditions for institution i. Section 3.A.2 in the appendix contains a detailed outline of the method to estimate (3.4).

3.3.3 Co-crash probability

The fourth measure of systemic risk is the so-called co-crash probability (CCP). It is derived from extreme value theory and used, for example, by De Jonghe (2010). CCP measures the likelihood of a large decline of an institution's stock price jointly with an extreme downturn of market performance. We use multivariate extreme value theory to estimate the *joint* probability of such a rare event of extreme stock return declines, R_{it}, and market portfolio

[15] The value at risk VaR^{q}_{it} of institution i is implicitly defined by $\mathbb{P}\{X_{it} \leq VaR^{q}_{it}\} = q$.

return declines, R_{mt}, on day t. The co-crash probability is of the type

$$\text{Prob}[R_{it} < x_i \cap R_{mt} < x_j], \tag{3.5}$$

where x_i and x_j are the threshold levels that denote the extreme event.

The estimation procedure of (3.5) is outlined in detail in Chapter 2 of this book. Note that in our estimation procedure, which is based on the work of Draisma et al. (2004) and Drees et al. (2004), we are not required to specify the threshold values x_i and x_j. These values are determined endogenously by the estimation procedure that aims to minimise the bias in estimating (3.5), and has the added advantage that the researcher does not specify, which events are regarded as extreme events.

3.3.4 Troubled Asset Relief Program

The final measure of systemic risk is a simple indicator of whether a financial institution tapped into the so-called TARP funds. Duchin and Sosyura (2012,0) show that not all banks that applied for TARP were also granted equity. Similar to Fahlenbrach and Stulz (2011), we therefore argue that the use of these emergency funds indicates which banks were considered important enough by the treasury to receive support.

3.4 Results

Table 3.3 shows descriptive statistics for all five measures of systemic risk as well as idiosyncratic performance measures. Volatility risk is calculated by taking the average of monthly calculated standard deviations of the total return index for each institution in the sample from July 2007 through December 2008. Returns on assets and equity are calculated as explained in Table 3.1 and buy-and-hold returns are obtained as in Fahlenbrach and Stulz (2011). Reflecting the considered crisis period, profitability measures are negative, thereby illustrating the strain on the financial system during July 2007 and December 2008.

Table 3.3. **Descriptive statistics of performance measures**

variable		mean	sd	N	p25	p50	p75
Idiosyncratic performance measures							
Volatility risk	%	0.14	0.09	92	0.10	0.12	0.15
RoA	%	-1.61	3.98	83	-3.94	-0.83	1.03
RoE	%	-4.79	16.60	83	-13.70	-1.89	7.50
Buy & hold returns	%	-30.83	15.11	79	-42.43	-29.40	-19.57
Systemic risk measures							
SCS_1	%	0.91	2.83	92	0.03	0.08	0.24
SCS_2	%	0.89	2.79	92	0.03	0.08	0.23
$\Delta CoVaR$	%	-1.54	0.72	92	-2.07	-1.41	-1.05
CCP	bp	159.45	64.51	91	110.59	157.93	200.73
TARP recipient	$\{0,1\}$	0.49	0.50	92	0	0	1

Notes: Table lists descriptive statistics across institutions for performance measures and systemic risk variables for the period July 2007 through December 2008. Volatility risk is the average of monthly calculated standard deviations of the total return index for each institution in the sample from July 2007 through December 2008. Buy and hold returns, are the total returns associated with owning a stock through this period. SCS_1 denotes the capital shortfall according to Brownlees and Engle (2012) and SCS_2 is the parsimonious estimate suggested by Acharya et al. (2012). $\Delta CoVaR$ is the conditional value at risk measure of Adrian and Brunnermeier (2011). CCP stands for the joint probability of the event where both the institution and the market experience an extreme negative return. TARP recipient denotes a dummy that indicates '1' if the institution received support from the Tarp or not '0'.

Both SCR measures are in line with the summary statistics reported in Acharya et al. (2012) and Brownlees and Engle (2012). The mean of the $\Delta CoVaR$ measure is also similar to the -1% reported in Adrian and Brunnermeier (2011). The joint co-crash probabilities of the institutions' returns and the market index returns average 159 basis points and have a standard deviation of 65 basis points between July 2007 and December 2008.

3.4.1 Conventional performance

Table 3.4 shows the results from OLS regressions that explain conventional profitability-based performance measures during the crisis with executives' compensation components from 2006. We focus on cash bonuses as a share of total salary to gauge short-term incentives, ownership shares as the classical alignment device between principals and agents, and equity incentives measured by the portfolio risk of the manager in terms of volatility sensitivity. Correlations between explanatory variables are presented in Table 3.B.3.

Table 3.4. **Performance and past executive compensation**

Dependent variable:	*RoA*	*RoA*	*RoA*	*RoA*	*RoE*	*Buy & hold return*
	(1)	(2)	(3)	(4)	(5)	(6)
CEO compensation						
Cash bonus / Salary	0.001	-0.016		-0.016	-0.131	0.128
	[0.041]	[0.038]		[0.044]	[0.178]	[0.212]
Percentage ownership	0.150**	0.035		0.042	0.223	-0.610
	[0.060]	[0.071]		[0.071]	[0.303]	[0.400]
non-CEO compensation						
Cash bonus / Salary			0.006	-0.001	0.043	0.269
			[0.060]	[0.080]	[0.326]	[0.303]
Percentage ownership			-0.053	-0.298	-0.804	3.952
			[0.720]	[0.742]	[2.943]	[3.456]
Overall compensation						
Black-Scholes volatility of equity	2.056	3.224	1.275	3.566	2.194	-2.843
	[4.249]	[3.995]	[3.960]	[3.997]	[6.124]	[3.273]
Institution variables						
RoA		0.035	0.029	0.038		
		[0.031]	[0.035]	[0.035]		
RoE					0.013	
					[0.020]	
Buy-and-hold return						-0.023
						[0.118]
Book to Market ratio		-5.655**	-6.702***	-5.675**	-8.503**	-6.249**
		[2.675]	[2.407]	[2.720]	[4.485]	[3.093]
log(Market value)		0.065	-0.096	0.051	0.345	-1.793
		[0.373]	[0.403]	[0.407]	[1.655]	[1.319]
Total capital ratio		-0.003	0.003	-0.004	0.004	0.138
		[0.020]	[0.020]	[0.021]	[0.078]	[0.094]
Constant	-2.328**	-0.309	1.810	-0.196	0.600	-4.964
	[1.051]	[3.782]	[3.971]	[4.065]	[16.657]	[13.314]
Observations	83	82	83	82	82	78
R^2	0.040	0.144	0.156	0.144	0.148	0.135
Adjusted R^2	0.004	0.063	0.078	0.037	0.042	0.021

Notes: Table reports cross-sectional regression results, ordinary least squares, of an institution's return on assets calculated for the period July 2007 through December 2008 on executive compensation variables and controls that cover the fiscal year 2006. The last two columns' specifications have return on equity as dependent variable for the period July 2007 through December 2008, and buy-and-hold total returns for the institution's stock which covers the same period. The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

The first two columns in Table 3.4 show that the cross-sectional dispersion in RoA during the crisis is primarily explained by firm-specific factors rather than any of the five executive compensation traits. Specifically, larger book-to-market ratios prior to the crisis depress profitability, as in Fahlenbrach and Stulz (2011). Larger cash bonuses in 2006 exhibit in no specification any significant correlation with profitability during the crisis. Larger CEO ownership is also insignificant when controlling for firm-specific traits. Finally, we also do not find a significant effect of equity portfolio risk in the managers' portfolios as in the conventional pay-performance literature.[16]

Columns (3) and (4) tests whether non-CEO executive pay matters, as suggested by Kim et al. (2011). Contrary to their study of stock price crashes among non-financial firms, we do also not find any evidence that bank RoA is significantly influenced by non-CEO pay. To compare our results with Fahlenbrach and Stulz (2011), we show in columns (5) and (6) results that explain the cross-sectional variation in RoE and buy-and-hold returns. Only book-to-market ratios exhibit (negative) explanatory power, thereby confirming their results.

3.4.2 Systemic and idiosyncratic risk

The absence of a relationship between executive compensation and idiosyncratic bank performance during the crisis confirms previous evidence in Fahlenbrach and Stulz (2011) and Acrey et al. (2011). Next, we turn to the regressions explaining the five alternative systemic risk measures. Table 3.5 shows cross-sectional estimations specifying the contribution to systemic capital shortfall as the dependent variable in columns (1) through (5). Next to compensation components, we specify bank-specific controls for the profitability, value, and size of the banking firm similar to Fahlenbrach and Stulz (2011).

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[16] Equity risk denotes a standard deviation volatility estimate of equity calculated over 60 months and derived from implied Black-Scholes values for options.

Table 3.5. **Contribution to systemic risk and executive compensation**

	Systemic Capital Shortfall					Additional systemic risk measures and volatility risk			
Method:	*OLS*	*OLS*	*OLS*	*OLS*	*IV*	*OLS*	*OLS*	*OLS*	*OLS*
Dependent variable:	SCS_1	SCS_1	SCS_1	SCS_2	SCS_2	$\Delta CoVaR$	CCP	$Tarp$ $Risk$	*Volatility*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEO compensation									
Cash bonus / Salary	0.108**		-0.060	-0.059	-0.059	-0.036***	-1.565**	-0.006	-0.001
	[0.041]		[0.067]	[0.066]	[0.045]	[0.011]	[0.743]	[0.004]	[0.001]
Percentage ownership	0.061		0.047	0.046	0.062	0.035**	-1.548	0.003	0.003*
	[0.054]		[0.051]	[0.051]	[0.056]	[0.013]	[1.237]	[0.017]	[0.002]
non-CEO compensation									
Cash bonus / Salary		0.206***	0.255**	0.240**	0.189**	0.049***	2.622**	0.018**	0.002*
		[0.073]	[0.113]	[0.112]	[0.091]	[0.016]	[1.088]	[0.007]	[0.001]
Percentage ownership		0.454	0.299	0.292	-0.012	-0.397***	-2.022	-0.071	-0.038*
		[0.493]	[0.453]	[0.449]	[0.562]	[0.149]	[12.685]	[0.144]	[0.021]
Overall compensation									
Black-Scholes volatility	2.735	0.622	1.239	1.264	2.219	0.488	128.731	-0.647	0.093
of equity	[2.181]	[1.781]	[1.677]	[1.664]	[2.349]	[0.793]	[81.930]	[0.592]	[0.071]
Institution variables									
RoA	-0.002	-0.010	-0.007	-0.006	-0.006	0.001	2.524***	0.002	-0.000
	[0.031]	[0.028]	[0.025]	[0.025]	[0.029]	[0.010]	[0.688]	[0.013]	[0.001]
Book to Market ratio	3.066**	2.041**	2.718**	2.696**	2.871**	-0.089	-1.174	-0.222	0.126*
	[1.205]	[1.013]	[1.226]	[1.240]	[1.302]	[0.414]	[36.921]	[0.269]	[0.074]
log(Market value)	1.233***	0.988**	1.066**	1.066**	1.192**	-0.221***	20.253***	-0.001	-0.010
	[0.392]	[0.376]	[0.407]	[0.412]	[0.448]	[0.077]	[5.077]	[0.044]	[0.008]
Total capital ratio	-0.025**	-0.016*	-0.018*	-0.018*	-0.021*	0.006*	0.139	-0.004	-0.001
	[0.011]	[0.010]	[0.009]	[0.009]	[0.011]	[0.003]	[0.317]	[0.004]	[0.001]
Constant	-11.103***	-8.444**	-9.540**	-9.535**	-10.713**	0.030	-46.523	0.805*	0.166**
	[3.650]	[3.325]	[3.758]	[3.800]	[4.152]	[0.772]	[62.613]	[0.463]	[0.071]
Observations	78	79	78	78	78	81	78	83	78
R^2	0.531	0.578	0.596	0.585	0.584	0.334	0.388	0.094	0.166
Adjusted R^2	0.485	0.536	0.543	0.530		0.249	0.307	-0.018	0.056
H_0: Underidentifcation					14.798*				
Hansen J statistic					6.793				

Notes: Table reports cross-sectional regression results, ordinary least squares, of various systemic risk measures on past characteristics of institutions. Column (7) displays the marginal effects of a logit regression. The systemic risk measures are calculated for the period July 2007 through December 2008 and executive compensation variables and other controls cover the fiscal year 2006. The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level. Identification in the specification in (5) is achieved by having the regressors uncorrelated with the product of heteroskedastic errors (Lewbel, 2012), we specify the non-CEO compensation variables 'Cash bonus / Salary' as endogenous. The test statistic for the Underidentification test is Chi-squared distributed with degrees of freedom equal to one plus the number of excluded instruments minus endogenous regressors (Kleibergen and Paap, 2006).

Columns (1) to (3) specify SCS calculated according to Brownlees and Engle (2012), which allows for time-variant return correlation. Column (4) and (5) features the SCS measure of Acharya et al. (2012) based on a parsimonious calculation of marginal expected shortfalls that uses the average return for those days in which the market performed 'bad'.

Contrary to the profitability regressions, all four regressions show that the level of cash bonus payments relative to fixed salary influences *SCS* significantly positive. Recall that *SCS* denotes each individual institution's contribution to the total quantum of systemic risk, which is on average around 90 basis points (see Table 3.3). The result in column (1) implies that an increase in the cash bonus ratio for CEOs by one increases this contribution by 11 basis points. The results in column (2) show that non-CEO bonus hikes have an even larger effect of 21 basis points. Thus, higher bonus components in total compensation of bank executives prior to the crisis had an undesirable positive effect on systemic risk, which is in line with the detrimental effects of short-term incentives stressed in Jensen (2004), Bolton et al. (2006), and Freixas and Rochet (2013).

The joint specification of bonus shares of CEOs and non-CEOs in column (3) shows, however, that it is the cash compensation of the latter that matter for systemic risk according to systemic capital shortfall. Whereas the coefficient of CEO bonus shares turns insignificant, the effect for non-CEOs increases to 26 basis points. This result underscores the argument of Diamond and Rajan (2009), Kim et al. (2011), and The Economist (2012) that CEOs of large, complex financial institutions might not even be able to discipline other high-powered managers. Incentives of the latter to take excessive systemic risk appear to crowd out any potentially aligned incentives of the CEO itself. Thus, any regulation aiming to restrict only CEOs of banks might fall short to tame systemically relevant financial institutions as argued for by Freixas and Rochet (2013).

Column (4) shows that this relationship is not due to the permission of changing return correlations underlying the *SCS* measure by Brownlees and Engle (2012). Here, we specify the parsimonious systemic risk contribution according to Acharya et al. (2012), which confirms that only non-CEO bonus shares exert a significantly positive, and economically relevant effect on systemic risk formation.

Other managerial compensation components, in turn, remain insignificant. More skin in the game as reflected by the percentage ownership share of both CEOs and non-CEOs does not influence systemic risk. Likewise, higher risks in the equity portfolio of managers does also not induce more systemic risk taking. Overall, we find therefore little evidence that aligning incentives of managers through ownership in the vein of Jensen and Murphy (1990) is effective to curtail systemic risk formation.

Column (5) presents the same specification as in Column (4), but differs in the sense that we instrumented the Cash Bonus over Salary of non-CEO executives. Despite the use of control variables the compensation variables may still be endogenous as a result of third factors that potentially drive both systemic risk formation as well as executives' compensation schemes. Some features of the firm are hard to control for but are potentially correlated with the explanatory variables. In particular when it comes to factors that are hard to measure or suffer from measurement error such as cultural factors. In response to these issues we employ the method proposed by Lewbel (2012) where identification is achieved by having the regressors uncorrelated with the product of heteroskedastic errors. This approach is likely to be somewhat less reliable then identification based upon the use of appropriate instruments. However, these instruments must be uncorrelated with the error term and at the same time must exhibit meaningful correlations with the compensation data. In light of the current ongoing debate on how to measure systemic risk in which no consensus is reached yet as to what exactly causes systemic risk formation, we retain a skeptical view with regard to availability of plausible identifying restrictions and resort to identification based on the exogeneity assumption of higher moments of the error term. Results in Column (5) do not differ substantially from Column (4), and corroborate the finding that non-CEO bonus shares exert a significantly positive and economically relevant effect on systemic risk formation. Tests for over and under identification provide evidence that supports the validity of the identification strategy.

An important caveat on the generalizability of these results pertains to the challenge how to measure systemic risk. We therefore show the relationship between managerial compensation and firm traits with three alternative indicators in columns (6) through (8). With the exception of $\Delta CoVaR$, the detrimental effects of short-term cash incentives for non-CEOs is confirmed. Both the tail risk of a co-crash probability between financial institutions and the market as well as the likelihood to tap TARP funds during the crisis respond positively to higher cash compensation of non-CEOs prior to the crisis. Likewise, the absence of risk-reducing effects of more skin in the game is also confirmed. These results therefore indicate that despite the challenges to gauge systemic risk, especially short-term cash incentives among non-CEOs deserve closer attention.

The results for $\Delta CoVaR$ warrant caution, the inference depends greatly on how we define systemic risk. Recall that lower values of $\Delta CoVaR$ indicate a higher sensitivity of the systems value at risk with respect to the distress of an individual institution. Contrary to all other specifications, our results indicate that both cash compensation as well as equity stakes of CEOs correlate significantly with this measure of systemic risk. Specifically, the results indicate contrary to the findings for SCS, CCP, and simple TARP indicators that larger cash bonuses of CEOs increase the system's sensitivity whereas more skin in the game reduce it. This result therefore suggests that also CEOs compensation is of relevance. Regarding non-CEO compensation, however, we also find that larger cash components actually increase $\Delta CoVaR$ (i.e. reduce systemic risk sensitivity) whereas larger equity stakes of non-CEOs have the opposite effect. The divergent inference based on this measure of systemic risk is interesting and further research on why popular measures differ, such as SCS and $\Delta CoVaR$, is important.

Column (9) shows that except for $\Delta CoVaR$, systemic risk measures gauge something else than idiosyncratic risk. Both the bonus share as well as a larger percentage ownership by non-CEOs affects bank-specific risk as expected on the basis of agency theory, albeit with less statistical significance and lower magnitude compared to systemic risk regressions. Whereas larger short-term bonuses increase volatility risk significantly, a larger equity stake of managers aligns interests with shareholders to the extent that volatility risk is reduced. The risk of managers' equity portfolios remains insignificant. Thus, classical instruments to solve agency conflicts may work for idiosyncratic risks in the financial industry, but not necessarily for systemic risk.

One potential concern is that not all the financial firms sampled are banks, but also include financial services firms that might not be subject to the incentives borne out by, for example, deposit insurance. Table 3.6 therefore replicates the baseline results for the approximately 60 banks only.

Table 3.6. **Systemic risk and executive compensation for banks only**

Dependent variable:	SCS_1	SCS_1	SCS_1	SCS_2	$\Delta CoVaR$	CCP	$Tarp$	*Volatility Risk*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CEO compensation								
Cash bonus / Salary	0.103**		-0.053	-0.051	-0.035***	-1.583**	-0.009***	-0.001
	[0.041]		[0.067]	[0.066]	[0.009]	[0.626]	[0.003]	[0.001]
Percentage ownership	0.095		0.073	0.073	0.048***	-1.834	-0.015	0.002
	[0.065]		[0.063]	[0.063]	[0.017]	[1.681]	[0.016]	[0.002]
non-CEO compensation								
Cash bonus / Salary		0.198***	0.235**	0.220*	0.039**	2.461**	0.026***	0.002*
		[0.073]	[0.111]	[0.111]	[0.016]	[1.148]	[0.007]	[0.001]
Percentage ownership		1.381	1.371	1.365	-0.145	28.387	-0.119	-0.088*
		[0.825]	[0.868]	[0.871]	[0.272]	[21.429]	[0.224]	[0.048]
Overall compensation								
Black-Scholes volatility of equity	1.532	-1.588	0.187	0.254	2.380**	219.807	-2.701***	0.096
	[3.742]	[2.842]	[2.857]	[2.842]	[1.041]	[138.786]	[0.682]	[0.123]
Institution variables								
RoA	-0.007	-0.035	-0.031	-0.031	0.002	1.643	-0.012	0.001
	[0.036]	[0.043]	[0.031]	[0.030]	[0.012]	[0.995]	[0.011]	[0.002]
Book to Market ratio	3.490**	1.936	3.091**	3.063*	0.381	-4.458	-0.692**	0.139
	[1.478]	[1.277]	[1.525]	[1.545]	[0.553]	[50.788]	[0.300]	[0.100]
log(Market value)	1.396***	1.188***	1.316***	1.316**	-0.140	21.989***	-0.052	-0.017
	[0.432]	[0.436]	[0.487]	[0.493]	[0.094]	[6.549]	[0.048]	[0.013]
Total capital ratio	-0.025*	-0.008	-0.013	-0.012	0.005	0.409	0.005	-0.001
	[0.015]	[0.014]	[0.012]	[0.012]	[0.003]	[0.361]	[0.004]	[0.001]
Constant	-12.498***	-9.761**	-11.799**	-11.799**	-1.348	-82.944	1.919***	0.235*
	[4.081]	[3.832]	[4.646]	[4.702]	[1.064]	[92.425]	[0.530]	[0.119]
Observations	59	60	59	59	61	59	61	59
R^2	0.561	0.610	0.631	0.620	0.370	0.409	0.217	0.204
Adjusted R^2	0.500	0.557	0.563	0.550	0.258	0.300	0.079	0.058

Notes: Table reports cross-sectional regression results, ordinary least squares, of various systemic risk measures on past characteristics for banks only. Column (7) displays the marginal effects of a logit regression. The systemic risk measures are calculated for the period July 2007 through December 2008 and executive compensation variables and other controls cover the fiscal year 2006.The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

Results are virtually identical regarding significance, magnitude, and direction compared to those shown in Table 3.5. We therefore continue to assess the entire sample of financial institutions, and refer to them synonymously as banks.

In sum, systemic risk responds differently to compensation traits compared to idiosyncratic risk. Especially short-term cash compensation of non-CEOs seems to induce systemic risk taking. Whereas most systemic risk measures suggest this relationship, the deviating results for $\Delta CoVaR$ emphasize the importance how to measure systemic risk for policy making.

3.4.3 Robustness

Extremely important banks

Henceforth, we focus on the SCS with time-variant correlation as our main measure of systemic risk. An important feature of the systemic risk indicator SCS, but also others, that is shown in Table 3.B.2 of the appendix is the large skew across banks. Put differently, the four most important contributors to systemic capital shortfall account for just about half of the entire systemic risk quantum in the system.

We argue, however, that these four very large contributors to systemic risk are not outliers in the classical sense that should be excluded from the analysis. The result underlines instead the skewed industry structure where fairly few financial firms account for the major share of activity, a phenomenon that is not restricted to the financial industry (see Gabaix, 2011, for the pervasive presence of Zipf's Law in finance and economics). Accordingly, we consider it plausible that also the major share of aggregate systemic risk is mostly accounted for by only relatively few, very important banks. To accommodate, however, the non-normal distribution of SCS, we show in Table 3.7 results where we regress compensation and other controls on the log of SCS.

Table 3.7. **Contribution to log scaled systemic risk and executive compensation**

Dependent variable:	$log(SCS_1)$ (1)	$log(SCS_1)$ (2)	$log(SCS_1)$ (3)	$log(SCS_2)$ (4)
CEO compensation				
Cash bonus / Salary	0.012***		-0.007**	-0.007*
	[0.004]		[0.003]	[0.004]
Percentage ownership	-0.046*		-0.051*	-0.048**
	[0.027]		[0.027]	[0.024]
non-CEO compensation				
Cash bonus / Salary		0.025***	0.030***	0.028***
		[0.006]	[0.006]	[0.007]
Percentage ownership		0.068	0.164	0.190
		[0.207]	[0.191]	[0.179]
Overall compensation				
Black-Scholes volatility of equity	1.017	0.010	0.701	0.872
	[0.787]	[0.704]	[0.727]	[0.748]
Institution variables				
RoA	0.030*	0.026	0.028	0.029**
	[0.016]	[0.019]	[0.017]	[0.014]
Book to Market ratio	2.326***	2.580***	2.296***	2.261***
	[0.464]	[0.498]	[0.466]	[0.464]
log(Market value)	1.016***	1.020***	1.002***	1.011***
	[0.048]	[0.054]	[0.052]	[0.052]
Total capital ratio	-0.039***	-0.039***	-0.038***	-0.038***
	[0.005]	[0.005]	[0.004]	[0.004]
Constant	-11.184***	-11.265***	-11.038***	-11.154***
	[0.594]	[0.609]	[0.612]	[0.603]
Observations	78	79	78	78
R^2	0.931	0.925	0.934	0.936
Adjusted R^2	0.924	0.918	0.925	0.927

Notes: Table reports cross-sectional regression results, ordinary least squares, of various systemic risk measures on past characteristics of institutions. Column (7) displays the marginal effects of a logit regression. The systemic risk measures are calculated for the period July 2007 through December 2008 and executive compensation variables and other controls cover the fiscal year 2006.The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

The results corroborate the positive effect of non-CEO cash bonuses on systemic risk contribution. The semi-elasticity of the cash bonus share with respect to SCS is 0.03. That is, increasing the ratio of cash bonuses to the fixed salary component by 1 percentage point increases systemic risk by 3 basis points, which is a reasonably important effect in light of mean *SCS* of around 90 basis points.

In addition, the semi-log specification indicates that both larger cash bonuses and higher equity stakes for CEOs actually reduce systemic risk taking. The latter result is in line with the notion that skin in the game disciplines managers. Certain classical instruments to align incentives between owners and managers may therefore also be useful to align the interest of the public to contain systemic risks with those of managers. Note, however, the confirmation of diverging effects between CEOs and non-CEOs. The results from the semi-log model corroborate that a firmer understanding potential intra-firm agency conflicts require further theoretical and empirical research to inform policy.[17]

Compensation and systemic risk over time

Another potential concern is that the relationship between cash components of non-CEOs and *SCS* is driven by extreme market movements in certain phases during the crisis. Table 3.8 shows therefore separate regressions for each quarter after the first concerted liquidity provision by central banks in q3:2007.

[17] Clearly, especially for financial firms more granular compensation data on actual risk takers, e.g. traders and brokers, would be desirable to investigate. Such data is unfortunately not available for this sample. Instead, we attempted to separate certain executive functions that should be pivotal in influencing systemic risk-taking, such as Chief Risk Officers and Chief Financial Officers. Unfortunately, the data does not permit a sufficiently precise identification of these functions. Out of the 92 firms and 412 non-CEO executive observations, we could infer on the basis of sparsely filled job titles only for less than 25% of the firms the aforementioned functions.

Table 3.8. **Systemic Capital Shortfall throughout the Global Financial Crisis**

Dependent variable:	SCS_1					
Quarter:	2007 - quarter 3	2007 - quarter 4	2008 - quarter 1	2008 - quarter 2	2008 - quarter 3	2008 - quarter 4
	(1)	(2)	(3)	(4)	(5)	(6)
CEO compensation						
Cash bonus / Salary	-0.132*	-0.101	-0.069	-0.070	-0.065	-0.035
	[0.078]	[0.081]	[0.070]	[0.070]	[0.066]	[0.062]
Percentage ownership	0.045	0.046	0.048	0.048	0.048	0.047
	[0.051]	[0.051]	[0.052]	[0.051]	[0.051]	[0.050]
non-CEO compensation						
Cash bonus / Salary	0.352***	0.326**	0.283**	0.283**	0.262**	0.183*
	[0.125]	[0.129]	[0.117]	[0.117]	[0.112]	[0.107]
Percentage ownership	0.250	0.254	0.257	0.253	0.247	0.226
	[0.437]	[0.443]	[0.446]	[0.443]	[0.436]	[0.424]
Overall compensation						
Black-Scholes volatility of equity	1.572	1.509	1.398	1.386	1.367	1.378
	[1.700]	[1.752]	[1.741]	[1.731]	[1.701]	[1.679]
Institution variables						
RoA	-0.012	-0.012	-0.012	-0.012	-0.012	-0.011
	[0.026]	[0.026]	[0.026]	[0.026]	[0.025]	[0.024]
Book to Market ratio	2.586**	2.588**	2.642**	2.619**	2.599**	2.473**
	[1.119]	[1.121]	[1.177]	[1.171]	[1.158]	[1.153]
log(Market value)	1.081***	1.078***	1.081**	1.073**	1.071**	1.068**
	[0.403]	[0.406]	[0.415]	[0.413]	[0.406]	[0.403]
Total capital ratio	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Constant	-9.644**	-9.612**	-9.627**	-9.555**	-9.521**	-9.410**
	[3.710]	[3.733]	[3.820]	[3.796]	[3.732]	[3.700]
Observations	78	79	78	78	81	78
R^2	0.616	0.607	0.609	0.609	0.604	0.567
Adjusted R^2	0.565	0.555	0.556	0.557	0.551	0.509

Notes: Table reports cross-sectional regression results, ordinary least squares, of an institution's contribution to systemic capital shortfall calculated for the quarters in the period July 2007 through December 2008 on executive compensation variables and controls that cover the fiscal year 2006.The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

The results show that the effect of cash compensation of non-CEO traits at year-end 2006 was strongest in the first crisis quarter considered and declined somewhat over time. The absence of ownership or equity portfolio effects as well as CEO payment effects is also confirmed. Thus, the importance of potentially negative effects of non-CEO cash compensation seems fairly robust and not due to specific time periods.

In Table 3.9 we evaluate the implications of compensation schemes prior to the fiscal year 2006, while keeping the institutional controls fixed for the year 2006. Results are in line with the findings reported in Table 3.5 and indicate that the effect of cash compensation for non-CEOs is robust across fiscal years prior to 2006. Note that the drop in observations in columns (1) and (2) highlights that compensation items are reported more sparsely than for the years 2004 and later. Furthermore, observations on percentage ownership data for non-CEOs are mainly not reported and are therefore excluded from the analysis.

Table 3.9. **Systemic Capital Shortfall and past executive compensation**

Dependent variable:	SCS_1			
Compensation for the year	2002	2003	2004	2005
	(1)	(2)	(3)	(4)
Compensation in considered year				
CEO compensation				
Cash bonus / Salary	-0.169**	0.215	0.050	-0.093
	[0.067]	[0.183]	[0.215]	[0.064]
Percentage ownership	0.119**	0.130**	0.046	0.032
	[0.067]	[0.051]	[0.299]	[0.174]
non-CEO compensation				
Cash bonus / Salary	0.698***	0.307**	0.347***	0.398***
	[0.115]	[0.149]	[0.097]	[0.133]
Percentage ownership				
Overall compensation				
Black-Scholes volatility	4.361***	1.400	2.125	1.717
of equity	[1.548]	[2.726]	[1.983]	[1.889]
Controls for the fiscal year 2006				
Institution variables				
RoA	0.032	0.016	-0.056	-0.015
	[0.022]	[0.027]	[0.057]	[0.027]
Book to Market ratio	2.908**	2.885**	2.696**	2.115**
	[1.388]	[1.377]	[1.061]	[1.038]
log(Market value)	0.941**	0.892**	0.998**	0.928**
	[0.448]	[0.411]	[0.405]	[0.400]
Total capital ratio	-0.026***	-0.024*	-0.012	-0.013
	[0.010]	[0.014]	[0.011]	[0.009]
Constant	-9.609**	-8.643**	-9.400**	-8.403**
	[4.266]	[4.088]	[3.743]	[3.714]
Observations	54	60	67	74
R^2	0.801	0.701	0.602	0.607
Adjusted R^2	0.765	0.655	0.548	0.559

Notes: Table reports cross-sectional regression results, ordinary least squares, of an institution's contribution to systemic capital shortfall calculated for the period July 2007 through December 2008 on executive compensation variables and controls that cover the fiscal year 2006. The compensation variables correspond with the above mentioned fiscal years. The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Percentage ownership of non-CEOs is excluded because values are mainly missing. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

Corporate governance and imprinting conditions

The recurring result that non-CEO cash bonuses influence systemic risk significantly while CEO bonuses do not may be related to differences in the governance structure across financial firms. If the argument of Diamond and Rajan (2009) holds that some CEOs were unable to control their subordinates, stronger shareholder governance or more experience may mitigate the effect.

Table 3.10 provides further robustness checks concerning differences in the corporate governance and imprinting conditions of executives across banks that may explain cross-sectional differences in systemic risk taking during the crisis.

Table 3.10. **Corporate governance and imprinting conditions**

Dependent variable:	SCS_1				
	(1)	(2)	(3)	(4)	(5)
CEO compensation					
Cash bonus / Salary	-0.045	-0.059	-0.059	-0.068	-0.055
	[0.064]	[0.069]	[0.070]	[0.069]	[0.078]
Percentage ownership	0.040	0.025	0.040	0.041	0.030
	[0.076]	[0.055]	[0.048]	[0.052]	[0.080]
non-CEO compensation					
Cash bonus / Salary	0.228**	0.259**	0.254**	0.269**	0.257*
	[0.108]	[0.119]	[0.119]	[0.106]	[0.129]
Percentage ownership	0.601	0.287	0.374	0.228	0.462
	[0.650]	[0.509]	[0.521]	[0.434]	[0.735]
Governance indicators					
Governance index	-0.146**				-0.093
	[0.066]				[0.060]
CEO number of years		-0.115			-0.140
in the board		[0.272]			[0.317]
non-CEO average number of		0.496*			0.476
years in the board		[0.272]			[0.317]
CEO number of			-0.064		-0.220
positions held			[0.346]		[0.417]
non-Ceo average number of			0.684		0.521
positions held			[0.495]		[0.502]
Board size				0.329	0.604
in persons				[0.434]	[0.528]
Overall compensation					
Black-Scholes volatility	1.006	2.761	1.420	0.221	-0.033
of equity	[1.806]	[2.315]	[1.954]	[2.213]	[3.144]
Institution variables					
RoA	-0.014	-0.002	-0.017	-0.010	-0.020
	[0.040]	[0.024]	[0.027]	[0.029]	[0.043]
Book to Market ratio	3.168**	2.924**	2.816**	2.550**	3.339**
	[1.409]	[1.275]	[1.328]	[1.105]	[1.513]
log(Market value)	1.135**	1.113**	1.084**	1.014***	1.107***
	[0.436]	[0.421]	[0.414]	[0.380]	[0.414]
Total capital ratio	-0.019**	-0.020**	-0.016*	-0.016*	-0.016
	[0.009]	[0.010]	[0.009]	[0.009]	[0.011]
Constant	-8.872**	-11.678**	-10.277**	-10.601**	-13.720**
	[3.764]	[4.661]	[4.023]	[4.440]	[6.045]
Observations	67	78	78	78	67
R^2	0.619	0.610	0.604	0.602	0.644
Adjusted R^2	0.551	0.545	0.537	0.543	0.540

Notes: Table reports cross-sectional regression results, ordinary least squares, of an institution's contribution to systemic capital shortfall calculated for the period July 2007 through December 2008 on executive compensation variables and controls that cover the fiscal year 2006. The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. The governance index is obtained from Gompers et al. (2003). Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

In column (1) we specify the governance index of Gompers et al. (2003). This index ranges between 0 and 12 points and higher values indicate more shareholder right restrictions and thus more managerial power. The effects of managerial compensation are not affected when adding the G-index. Only larger cash components of non-CEOs remain to have a positive effect on SCS. Whereas the coefficient for the G-index is significantly negative when specified individually, the last column also shows that it does not influence systemic risk once specified jointly with further proxies of executives imprinting conditions.

To measure imprinting conditions and experience, we first specify in column (2) the average years that CEO and non-CEO executives served on the board of the financial firm. Executives may not be able to influence systemic risk preferences immediately after joining the firm if this requires a fundamental change in risk cultures. Alternatively, executives that served for a very long term already may desire to leave a 'footprint' and are thus willing to take very large bets only towards the end of their careers. Related, Gabbioneta et al. (2013) show that groups of professional regulators may become jointly overconfident and influence each other to facilitate mutual concealment of undesirable, or even illegal, actions. Longer terms on boards may potentially create in analogy an environment where executives mutually influence each other's excessive risk-taking. Neither effect is confirmed by our data since both coefficients are not or only weakly significant at the 10%-level.

Next, we control in column (3) for the experience of executives by specifying the number of positions held on boards prior to joining the financial institution they were employed at in 2006. Numerous appointments may indicate a richer pool of experience. Alternatively, executives that change frequently may lean more towards the pursuit of short-term incentives that come at the expense of systemic risks. Also these proxies do not correlate significantly with systemic capital shortfall between July 2007 and December 2008.

Finally, larger boards may be better suited to avoid excessively risky choices by a single individual, but they are also harder to coordinate. The board size specified in column (4) does not indicate any of such effects for systemic risk though while leaving the positive effect of larger cash compensation of non-CEOs intact.

In sum, column (5) shows that a number of corporate governance and imprinting proxies have no significant joint effect on systemic capital shortfall whereas the previously reported result for non-CEOs remains intact.

CEO and non-CEO compensation gaps

Another possible explanation why non-CEO incentives may matter for systemic risk taking could be the compensation gap relative to the CEO. On average, Table 3.2 shows that CEOs earn around twice as much as the average non-CEO board member. The larger these differences are the greater may be the incentive for non-CEOs to accept projects with higher systemic risks, if these are also associated with the option of promotion to higher ranks.

Table 3.11. **Contribution to systemic risk and compensation gaps**

Dependent variable:	SCS_1	SCS_2	$\Delta CoVaR$	CCP	$Tarp$
	(1)	(2)	(3)	(4)	(5)
CEO compensation					
Cash bonus / Salary	0.016	0.015	0.034	3.405	-0.032
	[0.314]	[0.309]	[0.044]	[2.760]	[0.028]
Percentage ownership	0.047	0.047	0.039***	-0.990	-0.000
	[0.056]	[0.056]	[0.014]	[1.312]	[0.019]
non-CEO compensation					
Cash bonus / Salary	0.259**	0.243**	0.051***	2.677**	0.018**
	[0.119]	[0.118]	[0.015]	[1.130]	[0.008]
Percentage ownership	0.130	0.133	-0.215	29.210	-0.310
	[0.674]	[0.672]	[0.289]	[22.577]	[0.222]
Interaction between compensation					
Cash bonus / Salary (CEO)	-0.002	-0.002	-0.002	-0.138*	0.001
× Cash bonus / Salary (non-CEO)	[0.009]	[0.009]	[0.001]	[0.073]	[0.001]
Percentage ownership (CEO)	0.026	0.025	-0.021	-3.783	0.031
× Percentage ownership (non-CEO)	[0.067]	[0.066]	[0.029]	[2.546]	[0.025]
Overall compensation					
Black-Scholes volatility	0.599	0.652	0.574	167.540*	-1.028
of equity	[2.382]	[2.364]	[0.920]	[98.867]	[0.764]
Institution variables					
RoA	-0.007	-0.007	-0.001	2.197***	0.004
	[0.029]	[0.029]	[0.012]	[0.612]	[0.013]
Book to Market ratio	2.761**	2.738**	-0.017	7.507	-0.254
	[1.285]	[1.293]	[0.424]	[36.752]	[0.272]
log(Market value)	1.031**	1.033**	-0.238***	19.972***	-0.003
	[0.405]	[0.413]	[0.083]	[5.896]	[0.048]
Total capital ratio	-0.020*	-0.019*	0.005	0.078	-0.004
	[0.011]	[0.011]	[0.004]	[0.303]	[0.005]
Constant	-9.155**	-9.166**	0.074	-60.580	0.938*
	[3.774]	[3.839]	[0.871]	[73.616]	[0.538]
Observations	78	78	81	78	83
R^2	0.598	0.587	0.364	0.421	0.117
Adjusted R^2	0.531	0.518	0.262	0.325	-0.019

Notes: Table reports cross-sectional regression results, ordinary least squares, of an institution's contribution to systemic capital shortfall calculated for the period July 2007 through December 2008 on executive compensation variables and controls that cover the fiscal year 2006.The variables under *non-CEO compensation* are mean values taken among non-CEO executives of an institution. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

Table 3.11 therefore shows results for all measures of systemic risk including an interaction term between CEO and non-CEO compensation components. The direct positive effects of cash shares among non-CEOs as well as the absence of ownership effects remains intact for all but the $\Delta CoVaR$

measure as before.

Larger gaps in terms of cash compensation and ownership shares between CEOs and non-CEOs, in turn, do not have a significant impact on virtually all of the five systemic risk measures. Only co-crash probabilities are weakly significant and negative for a larger cash compensation share of CEOs holding constant the share received by non-CEOs. In turn, however, the direct effect is now also insignificant and thus in line with the results for systemic capital shortfall as well as the simple TARP indicator. Overall, the results therefore lend little support to the notion of compensation-envy among lower tier executives to explain systemic risk taking of non-CEOs.

3.4.4 Compensation details and levels

Compensation components considered so far are fairly crude. Cash bonuses match with the short-termism problems pointed out in Bolton et al. (2006) and the potential ineffectiveness of aligned owner and agent incentives captured by equity stakes and equity incentives in the form of portfolio risk sensitivity. Table 3.12 provides a one-by-one consideration of separate compensation categories provided by the Execucomp database and the level of total pay.[18]

[18] We prefer to specify the log-level of total pay as a separate variable as opposed to using it as the denominator of compensation components. The first reason is to explicitly control for the stylised fact reported by Kaplan and Rauh (2010) that levels of pay may be exuberant in the financial industry. Second, the use of fixed salary components is consistent with Fahlenbrach and Stulz (2011).

Table 3.12. **Contribution to SCS_1 and alternative compensation**

	(1)	(2)	(3)	(4)	(5)	(6)
CEO compensation						
Cash bonus /	-0.058	-0.064	-0.047	-0.054	-0.058	-0.052
Salary	[0.069]	[0.073]	[0.030]	[0.070]	[0.067]	[0.067]
Non-equity incentives /		0.048				
Salary		[0.224]				
Value of stock grant /			-0.147			
Salary			[0.100]			
Value of option grant /				0.157		
Salary				[0.137]		
Total deferred earnings /					0.045	
Salary					[0.072]	
Other compensation /						-0.111
Salary						[0.135]
Percentage ownership	0.044	0.046	0.042	0.054	0.051	0.046
	[0.052]	[0.045]	[0.061]	[0.053]	[0.047]	[0.054]
log(Total Compensation)	0.235	0.137	0.580	0.207	0.091	0.283
	[0.369]	[0.413]	[0.476]	[0.370]	[0.402]	[0.378]
non-CEO compensation						
Cash bonus /	0.293**	0.372***	0.350***	0.290**	0.275**	0.280**
Salary	[0.123]	[0.108]	[0.076]	[0.128]	[0.122]	[0.123]
Non-equity incentives /		0.462				
Salary		[0.646]				
Value of stock grant /			0.716**			
Salary			[0.294]			
Value of option grant /				-0.314		
Salary				[0.289]		
Total deferred earnings /					-0.424	
Salary					[0.360]	
Other compensation /						-0.194
Salary						[0.354]
Percentage ownership	0.375	0.410	0.007	0.292	0.306	0.385
	[0.563]	[0.510]	[0.434]	[0.564]	[0.570]	[0.599]
log(Total Compensation)	-1.086	-1.463*	-2.207**	-1.066	-0.891	-1.062
	[0.826]	[0.845]	[0.845]	[0.791]	[0.768]	[0.826]
Overall compensation						
Black-Scholes volatility	2.866	2.123	2.578	2.994	2.371	3.022
of equity	[2.435]	[2.372]	[1.868]	[2.665]	[2.339]	[2.413]
Institution variables						
RoA	0.000	-0.007	0.039	0.006	-0.011	-0.000
	[0.033]	[0.029]	[0.037]	[0.031]	[0.034]	[0.033]
Book to market ratio	2.485**	1.979*	2.289**	2.601**	2.480**	2.665**
	[1.158]	[1.067]	[1.079]	[1.189]	[1.159]	[1.256]
log(Market value)	1.555**	1.530**	1.566***	1.580**	1.606**	1.555**
	[0.650]	[0.667]	[0.545]	[0.748]	[0.685]	[0.658]
Total capital ratio	-0.020**	-0.015	-0.026**	-0.019*	-0.018*	-0.020**
	[0.010]	[0.009]	[0.011]	[0.010]	[0.010]	[0.009]
Constant	-7.836**	-4.333	-3.124	-8.037*	-8.305**	-8.370**
	[3.097]	[2.960]	[3.170]	[4.132]	[3.283]	[3.381]
Observations	78	78	78	78	78	78
R^2	0.618	0.640	0.705	0.622	0.626	0.625
Adjusted R^2	0.554	0.565	0.645	0.544	0.549	0.548

Notes: Table reports cross-sectional regression results, ordinary least squares, of an institution's contribution SCR_1 to systemic risk formation calculated for the period July 2007 through December 2008 on executive compensation variables and controls that cover the fiscal year 2006. Heteroscedastic robust standard errors are reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1, 5 and 10 percent level.

Column (1) confirms the earlier result that cash bonuses prior to the crisis increased systemic risk formation between July 2007 and December 2008. The result that only non-CEO bonuses matter is corroborated.

Whereas the sheer level of CEO pay has no significant influence systemic risk, higher non-CEO pay levels reduce it significantly if cash bonuses are paired with other non-equity incentives or larger stock grants. Contrary to predictions of agency theory that skin in the game should reduce (excessive) risk appetite, we find however also that larger stock grants to non-CEOs increases systemic risk.

For the most part, however, both the level of pay as well as other compensation components except cash bonuses for non-CEOs are not statistically significant. Overall, the incentives borne out by the structure of bank executive compensation therefore seem more important compared to levels of pay as such.

3.5 Conclusion

We investigate empirically whether bank executive compensation prior to the financial crisis contributed to the formation of *systemic* risk among 92 U.S. financial firms. We measure systemic risk with five different indicators between July 2007 and December 2008: two versions of systemic capital shortfall (SCS, Acharya et al., 2012; Brownlees and Engle, 2012), $\Delta CoVaR$ (Adrian and Brunnermeier, 2011), co-crash probabilities derived with extreme value theory (De Jonghe, 2010), and a simple indicator if the financial institution received TARP funding.

In line with Fahlenbrach and Stulz (2011), we find no evidence of a relationship between CEO and non-CEO executive compensation in 2006 and idiosyncratic firm return performance during the crisis. However, we do find that cash bonus shares have a significant influence on all systemic risk measures and that the effects differ from those of managerial compensation on conventional idiosyncratic risk measures. Our results thus corroborate theoretical concerns about potentially hazardous short-term incentives (Bolton et al., 2006).

Importantly, this relationship is driven by non-CEO executive pay. CEO performance pay does not correlate with most systemic risk measures, again $\Delta CoVaR$ being the exception. This result indicates that CEOs are either not able or willing to effectively discipline all the management in large, complex financial institutions. Hence, any possible compensation regulation needs to consider senior management beyond the CEO. In light of the argument by Boot and Schmeits (2000) this dichotomous finding may arise from the differing objectives of executives. Whereas the CEO is concerned with the overall performance of the bank, the other executives may have a bias towards valuing their department or division's performance that may lead to excessive risk taking by non-CEO managers. This result remains intact after controlling for systemic risk in different quarters of the crisis, differences in corporate governance and imprinting conditions across banks, as well as wage gaps between CEOs and non-CEOs. Additional analysis where we specify non-CEO executive pay as endogenous yield the same insights.

Finally, it is important to note that the results are driven by a subset of large and systemically important banks. Four banks account for around half systemic capital shortfall, thereby underpinning the extremely skewed distribution in individual banks' contributions to systemic risk. At the same time, it is exactly this group of very important banks that compensated executives intensively by means of cash bonuses.

In sum, we complement recent studies like Fahlenbrach and Stulz (2011) who find little evidence of executive compensation effects on idiosyncratic as opposed to systemic risk. Executive compensation of non-CEOs correlates with most systemic risk measures, whereas CEO pay is not significantly correlated. This discrepancy of effects is important in the regulation of bank executive pay, and also calls for future research into potential agency conflicts inside financial firms.

3.A Systemic Risk Measures

3.A.1 Estimation of the Marginal Expected Shortfall

This section outlines the estimation procedure of the Marginal Expected Shortfall term represented by $\mathbb{E}[R_i^p | R_m^p < \kappa]$ or MES_i^p for short as denoted by (3.1). The procedure derives from the work of Rabemananjara and Zakoïan (1993) and Engle (2002).

Let institution i's log return on day t be denoted by r_{it}, and the market index by r_{mt}. The respective volatilities are σ_{it} and σ_{mt}, and the correlation between the two series is denoted by ρ_{it}. The model is specified as follows:

$$\begin{aligned} r_{mt} &= \sigma_{mt}\varepsilon_{mt}, \\ r_{it} &= \sigma_{it}\rho_{it}\varepsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it}, \\ \varepsilon_{mt}, \xi_{it} &\sim \mathcal{N}(\mathbf{0}, \boldsymbol{I}). \end{aligned} \tag{3.A.1}$$

Here, ε_{mt} and ξ_{it} are independent shocks in (3.A.1) with zero mean and unit variance. This dynamic system allows to infer the performance of the institution under changing market conditions. It helps to identify the institution's performance conditional on adverse market circumstances, such that a crisis period can be accounted for.

No closed form solution of the marginal expected shortfall over a horizon of p days exist. We use Monte Carlo simulation to estimate MES_{it}^p. Parameters in (3.A.1) are substituted with their estimates to simulate p pairs of daily returns:

$$\{r_{i,t+\tau-1}^s, r_{m,t+\tau-1}^s\}_{\tau=1}^{\tau=p},$$

where s indexes the Monte Carlo simulations. Thus, two random shocks are generated and filtered through the model to compute the returns for a particular day. Next, we calculate the cumulative return within the considered period as: and obtain the cumulative return for the market similarly. This procedure is repeated for all of the S simulations. The estimate of the marginal expected shortfall is then calculated as the institution's average cumulative return across those pairs where the market return is below the threshold κ, denoted by

$$\widehat{MES}_{i,t}^{p} = \frac{\sum_{s=1}^{S} R_{i,t:t+p-1}^{s} \mathbf{1}\{R_{m,t:t+p-1}^{s} < \kappa\}}{\sum_{s=1}^{S} \mathbf{1}\{R_{m,t:t+p-1}^{s} < \kappa\}}, \tag{3.A.2}$$

where $\mathbf{1}\{.\}$ is an indicator variable that equals one if the condition in braces is true and zero otherwise.

The parameters σ_{it}, σ_{mt} and ρ_{it} of system (3.A.1) are estimated by means of a two step maximum likelihood procedure (Engle, 2009). First, consistent volatility estimates are obtained from predictions of a GARCH class model specified for the log return processes. Second, a Dynamic Conditional Correlation (DCC) model is specified for standardized log returns of institution i and the market. The last step is necessary to obtain consistent estimates of the correlation coefficients between the two log returns series.

The idiosyncratic log return processes are modeled as follows. A standard GARCH process is specified for the conditional variance dynamics of the log return process that includes a TARCH term (Rabemananjara and Zakoïan, 1993). The TARCH term implies that the conditional variance is dependent on the state of past return realizations. The advantage is that the conditional covariance for the market log return can be larger in absolute size during for instance crises relative to regular periods. Formally, we specify for each log return series, as well for the market index:

$$\begin{aligned} & r_{it} = \alpha_i + \epsilon_{it}, \quad \epsilon_{it} \sim \mathcal{N}(0, \sigma_{it}), \quad \text{with} \\ & \sigma_{it}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{i,t-1}^2 + \gamma_{i2}\epsilon_{i,t-1}^2 \mathbf{1}\{\epsilon_{i,t-1} < 0\} + \gamma_{i3}\sigma_{i,t-1}^2, \end{aligned} \tag{3.A.3}$$

where $\mathbf{1}\{.\}$ denotes an indicator variable that equals one if the condition in braces is true and zero otherwise. The parameters of the processes are estimated with a quasi-maximum likelihood approach. Subsequently, the predicted values for σ_{it} serve as the parameter estimates of the volatility terms in (3.A.1).

A necessary step to calculate the correlation coefficients in (3.A.1) is to standardize the residuals of (3.A.3) with the predicted volatility terms. A DCC model is subsequently specified for the standardized residuals of the return process of institution i and the market. Let the standardized residuals be denoted by $\hat{\epsilon}_{it}$ and $\hat{\epsilon}_{mt}$, respectively for institution i and the market log return. In addition, the correlation matrix for the two series at day t can be denoted as:

$$\boldsymbol{Q}_{it} := \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix}.$$

A consequence of using standardized residuals over unstandardized residuals is that the off diagonal elements reflect unit variance. The off diagonal elements are equal to the correlation coefficient used at time t in (3.A.1). Let $\hat{\boldsymbol{\epsilon}}_{it} := [\hat{\epsilon}_{it}, \hat{\epsilon}_{mt}]^T$ and the correlation coefficient between the two series can be modeled as a multivariate GARCH process:

$$\begin{aligned} &\hat{\boldsymbol{\epsilon}}_{it} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{Q}_{it}), \quad \text{with} \\ &\boldsymbol{Q}_{it} = \boldsymbol{S}_i + \delta_{i1}\hat{\boldsymbol{\epsilon}}_{i,t-1}\hat{\boldsymbol{\epsilon}}_{i,t-1}^T + \delta_{i2}\boldsymbol{Q}_{i,t-1}, \end{aligned} \tag{3.A.4}$$

and $\boldsymbol{S}_i$ is restricted to be a postive definite matrix. The parameters of the process in (3.A.4) are, as for (3.A.3), also estimated with a quasi-maximum likelihood approach. The model's predictions for the correlation coefficient are used as parameter estimates for (3.A.1) to simulate log returns.

3.A.2 Estimation of $\Delta CoVaR$

We focus on growth rates of market-valued total financial assets as performance measure of institutions. We follow Adrian and Brunnermeier (2011) and let ME_{it} be the market value of bank i's equity, and LEV_{it} the ratio of total assets to book equity. The growth rate of market valued total assets is calculated by applying the market-to-book equity ratio to transform book-valued total assets into market valued assets,

$$X_{it} := \frac{ME_{it}LEV_{it} - ME_{it-1}LEV_{it-1}}{ME_{it-1}LEV_{it-1}}.$$

The market performance $X_{system,t}$ is the weighted average growth rate of all considered institutions. The average growth rate is constructed on a weekly basis and the weights are based on the proxy for the market value of total assets.

Additionally, a set of time-varying macroeconomic state variables are used to estimate (3.4). We use the same variables as Adrian and Brunnermeier (2011), which are described in Table 3.A.1.

Table 3.A.1. **Descriptive statistics of lagged state variables**

variable	**mean**	**sd**	**p25**	**p50**	**p75**
VIX	21.20	8.30	14.60	20.10	25.00
Liquidity spread	20.70	34.10	-5.20	10.30	57.80
Change in three-month T-bill rate	-0.60	12.40	-18.50	-0.30	6.00
Slope of yield curve	0.10	13.10	-17.30	0.10	20.90
Credit spread change	0.02	8.00	-10.30	0.020	12.60
Market return CRSP	0.14	2.80	-4.40	0.00	3.20
Real estate sector return	-0.10	3.40	-7.20	-0.10	9.10

Notes: Table lists descriptive statistics for the state variables used in the quantile regressions to estimate $\Delta CoVaR^{q}_{system|i}$, (3.4). Returns are reported in percentages, other variables in basis points. Variables are weekly observed in the period January 1992 through December 2011.

The volatility index *VIX* is used to capture the implied volatilities in the stock market as reported by the Chicago Board Options Exchange. A short term *liquidity spread* is calculated by taking the difference between the three-month repo rate and the three-month T-bill rate. The *change in three-month T-bill rate* is also included and obtained from the Federal Reserve Board. Additionally, the *slope of the yield curve* is obtained by subtracting the three-month T-bill rate from the ten-year T-bill rate. The change in the *credit spread* of BAA-rated bonds and the ten-year T-bill rate are included. Last, the weekly equity *market return from CRSP* and the *weekly real estate sector return* in excess of the market return.

Time-varying $CoVaR^q_{system,t|i}$ and VaR^q_{it} estimates are obtained for each institution and conditioned on a vector of state variables lagged by one week, $\boldsymbol{m}_{t-1}$. The following quantile regressions are executed for weekly observations to estimate the conditional performance generating processes associated with each institution:

$$\begin{aligned} X_{it} &= \alpha_i + \gamma_i \boldsymbol{m}_{t-1} + \varepsilon_{it}, \\ X_{system,t} &= \alpha_{system|i} + \beta_{system|i} X_{it} + \gamma_{system|i} \boldsymbol{m}_{t-1} + \varepsilon_{system,t|i}. \end{aligned}$$

The predicted values of the quantile regressions yield:

$$\begin{aligned} \widehat{VaR}^q_{it} &= \hat{\alpha}^q_i + \hat{\gamma}^q_i \boldsymbol{m}_{t-1}, \\ \widehat{CoVaR}^q_{system,t|i} &= \hat{\alpha}^q_{system|i} + \hat{\beta}^q_{system|i} \widehat{VaR}^q_{it} + \hat{\gamma}^q_{system|i} \boldsymbol{m}_{t-1}. \end{aligned}$$

The impact of a bank's distress on the system's value at risk (3.4) is estimated by

$$\Delta\widehat{CoVaR}^q_{system,t|i} = \hat{\beta}^q_{system|i} (\widehat{VaR}^q_{it} - \widehat{VaR}^{50\%}_{it}). \tag{3.A.5}$$

We calculate (3.A.5) on a weekly basis for each institution and set the critical level q at one percent. The estimation is carried out for the period January 1992 through December 2011. Within sample predictions are carried out to compute (3.A.5) for each week in the period July 2007 through December 2008. The average of the weekly observations in this period constitute the dependent variable for each institution used for analysis.

3.B Appended tables

Table 3.B.1. **Definitions of executive compensation variables**

Total Compensation	Total compensation (in thousands USD) as calculated under the 1992 reporting format: Total compensation comprises of the following: Salary, Cash Bonus, Total value of stocks granted, Total value of stock options granted, Total deferred earnings, and Other compensation.
Salary	The dollar value (in thousands) of the base salary earned by the executive officer during the fiscal year.
Cash bonus	The dollar value of a bonus (in thousands) earned by the executive officer during the fiscal year.
Non-equity incentives	Value of amounts (in thousands USD) earned during the year pursuant to non-equity incentive plans. The amount is disclosed in the year that the performance criteria was satisfied and the compensation was earned.
Value of stock grant	Value of stock-related (in thousands of USD) grants (e.g. restricted stock, restricted stock units, phantom stock, phantom stock units, common stock equivalent units etc.) that do not have option-like features. Valuation is based upon the value of shares that vested during the year as detailed in FAS123R. The amount here is the cost recorded by the company on its income statement as well as any amounts that were capitalized on the balance sheet for the fiscal year. This discloses the cost that was charged to the company (and thus to shareholders) for the year, as distinct from the grant date fair value of the award.
Value of option grant	Value of option-related awards (in thousands USD) (e.g. options, stock appreciation rights, and other instruments with option-like features). Valuation is based upon the value of options that vested during the year as detailed in FAS123R. The amount here is the cost recorded by the company on its income statement as well as any amounts that were capitalized on the balance sheet for the fiscal year. This column discloses the cost that was charged to the company (and thus to shareholders) for the year, as distinct from the grant date fair value of the award.
Total deferred earnings	Total aggregate earnings in deferred compensation plans in last fiscal year. Deferred compensation plans are aggregate earnings in non-tax-qualified deferred compensation plans during the year.
Other compensation	Other compensation received by the executive including perquisites and other personal benefits, termination or change-in-control payments, contributions to defined contribution plans (e.g. 401K plans), life insurance premiums, gross-ups and other tax reimbursements, discounted share purchases etc.
Value of total equity portfolio	Total value of subsequent items (in thousands USD) at fiscal year end.
Value of shares	Market value (in thousands USD) of shares held by the executive at Fiscal Year End.
Value of vested shares	Value realized on vesting (in thousands USD). Value of restricted shares vested during the year.
Value of exercisable options	Estimated value (in thousands USD) of in-the-money unexercised exercisable options. The estimated aggregate value of in-the-money vested options at fiscal year end, calculated based on the difference between the exercise price of the options and the close price of the company's primary issue of stock at year end.
Value of unexercisable options	Estimated value (in thousands USD) of in-the-money unexercised unexercisable options. The estimated aggregate value (in thousands USD) of in-the-money unvested options at fiscal year end, calculated based on the difference between the exercise price of the options and the close price of the company's primary issue of stock at year end.
Value of unvested restricted stock	Value of shares of restricted stock (in thousands of USD) held by the executive as of fiscal year end.
Black-Scholes volatility of equity	This is the volatility figure used in calculating Black-Scholes values for options. This is a standard deviation volatility calculated over 60 months.
Percentage ownership	Percentage of total shares owned
Percentage ownership, options excluded	Percentage of total shares owned, excluding options (if greater than one percent).
Years in boardroom	Denotes the number of years the executive held a function in the company's boardroom up and until the fiscal year 2006
Number of positions held during years in boardrooms	Denotes the number of positions held during the years in which the executive was present in the boardroom up and until the fiscal year 2006
Board size	Size of the board in persons
Governance index	Based on Gompers et al. (2003): every extra point reflects a provision that restricts shareholder rights on a scale from 0 to 12, i.e. increases managerial power.

Table 3.B.2. **Sampled institutions and systemic risk measures (in %)**

Name Institution	SCS_2	$\Delta CoVaR$	CCP (bp)	Tarp
Acadia Realty Trust	0.01	-0.76	140.58	no
American Express	1.27	-3.08	233.78	yes
Anchor Bancorp Wis.	0.04	-1.18	76.54	yes
Ass. Banc-Corp.	0.18	-1.14	59.86	no
Astoria Financial	0.19	-1.72	159.43	no
Avalonbay Comm.	0.07	-1.27	181.06	no
Bank Mutual	0.03	-2.18	125.65	no
Bank of America	15.12	-1.21	285.35	yes
Bank of Hawaii	0.09	-3.25	60.20	no
Bank of N-Y Mellon	2.04	-2.17	241.69	yes
Boston Properties	0.11	-1.89	182.73	no
Bristow Group	0.02	-1.73	186.27	no
Brookline Bancorp	0.02	-1.55	88.66	yes
Brunswick Bancorp	0.00	-0.50	0.00	no
Capital One Fin.	1.19	-0.97	144.53	yes
Cascade Bancorp	0.02	-1.14	162.90	yes
Central Pacific Fin.	0.05	-0.86	58.73	yes
Citigroup	17.97	-1.05	251.72	yes
City National	0.13	-2.40	215.42	yes
Cullen/Frost Bankers	0.12	-2.36	113.54	no
Dime Comm. Bancsh.	0.03	-2.42	157.93	no
Duke Realty	0.07	-1.57	151.81	yes
E-Trade Fin.	0.47	-1.23	102.54	no
East West Bancorp	0.09	-1.13	163.66	yes
Eastgroup Properties	0.01	-0.88	109.43	no
Equity Res. Trust	0.16	-1.49	157.36	no
Essex Property Trust	0.03	-1.50	131.54	no
Federated Investors	0.02	-0.94	200.73	no
Fifth third Bancorp	0.96	-3.31	135.98	yes
First Midwest Bancorp	0.07	-1.71	234.31	yes
First Niagara Fin. Gr.	0.07	-1.10	156.42	yes
Firstfed Financial	0.06	-0.91	58.23	no
Firstmerit	0.09	-1.83	231.68	yes
Franklin Bank	0.05	-0.89	88.71	yes
Franklin Bancorp .	0.13	-2.20	215.69	yes
Glacier Bancorp	0.04	-1.64	110.12	no
Goldman Sachs Gr.	9.17	-2.81	210.34	yes
Hanmi Financial	0.03	-0.77	108.19	no
Heritage Commerce	0.01	-0.95	127.42	yes
HF Financial	0.01	-2.35	33.49	yes
Highwoods Prop.	0.03	-1.21	140.47	no
Host Hotels & Resorts	0.10	-2.69	163.44	no
Huntington Bancsh.	0.44	-1.89	162.14	yes
Independent Bank	0.03	-1.10	110.59	yes
Istar Financial	0.13	-1.43	200.15	no
Janus Capital Group	0.04	-1.21	267.27	no
Jefferies Group	0.22	-1.52	101.21	no
JP Morgan Chase & Co.	2.58	-0.93	97.82	yes
Keycorp	0.85	-2.65	224.56	yes
Kilroy Realty	0.02	-1.30	106.58	no
Kimco Realty	0.10	-1.86	83.40	no
Legg Mason	0.08	-1.41	260.44	no
Lexington Realty	0.04	-0.22	82.77	no
LTC Properties	0.00	-0.80	163.46	no
Macerich Co.	0.08	-0.82	169.49	no
Mack Cali Realty	0.04	-1.24	159.40	no
Metlife	4.55	-2.48	130.63	no
Morgan Stanley	8.34	-1.27	303.38	yes
National Retail Prop.	0.02	-1.01	160.65	no
N-Y Comm. Bancorp	0.25	-1.18	252.79	no
Northern Trust	0.70	-2.30	328.73	yes
Park National	0.06	-1.48	188.55	yes
Pinnacle West Capital	0.07	-2.07	228.12	yes
Plum Creek Timber	0.06	-2.79	130.58	no
PNC Fin. Serv. Gr.	1.21	-2.87	169.45	yes
Potlatch	0.02	-0.71	126.13	no
Presidential Realty	0.00	0.01	56.91	no
Prosperity Bancsh.	0.05	-1.13	146.28	no
Public Storage	0.11	-1.87	195.25	no
Regions Fin.	1.14	-1.75	115.08	yes
Sapient	0.00	-1.46	122.65	no
SEI Investments	0.03	-0.89	243.39	no
Simon Prop. Gr.	0.29	-1.26	207.46	no
State Street	1.89	-1.53	135.55	yes
Sterling Bancorp.	0.02	-1.14	164.50	yes
Sterling Fin.	0.10	-1.99	88.42	yes
Suntrust Banks	1.46	-2.14	110.48	yes
Susquehanna Bancsh.	0.11	-1.52	223.00	yes
SVB Fin. Gr.	0.07	-2.94	178.57	yes
Synovus Fin.	0.28	-1.18	146.26	yes
TD Ameritrade Hold.	0.18	-1.28	290.45	no
Tetra Tech	0.01	-0.64	165.79	no
UCBH Holdings	0.11	-1.23	192.56	no
Umpqua Hold.	0.07	-0.49	170.88	yes
United Banksh.	0.00	-0.81	89.36	no
Vornado Realty Trust	0.02	-2.19	286.03	no
Washington Fed.	0.09	-2.26	99.89	yes
Webster Fin.	0.14	-0.98	185.76	yes
Wells Fargo & Co.	5.40	-3.54	213.50	yes
Westamerica Bancorp.	0.04	-1.26	118.16	yes
Wintrust Fin.	0.08	-2.08	149.12	yes
Zions Bancorp.	0.44	-1.41	131.94	yes

Table 3.B.3. Cross-correlation table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEO compensation									
(1) Cash bonus / Salary	1.000								
(2) Percentage ownership	-0.083	1.000							
non-CEO compensation									
(3) Cash bonus / Salary	0.822*	-0.094	1.000						
(4) Percentage ownership	-0.085	0.397*	-0.103	1.000					
Overall compensation									
(5) Black-Scholes volatility	0.041	0.385*	0.043	0.371*	1.000				
Institution variables									
(6) ROA	0.020	0.163	-0.013	0.166	0.059	1.000			
(7) Book to Market ratio	-0.020	-0.382*	-0.011	-0.164	-0.132	-0.166	1.000		
(8)*log*(Market value)	0.325*	-0.250*	0.419*	-0.250*	-0.233*	0.035	-0.178	1.000	
(9) Total capital ratio	-0.052	0.240*	-0.128	0.124	0.321*	0.435*	-0.045	-0.176	1.000

Notes: Table reports correlation coefficients between two variables listed in the most left column. Variables are indexed by the number preceding in between parentheses. Significance levels are

Chapter 4

Dueling Policies: Systemic Risk Taxation versus Constructive Ambiguity

> Deep in the human unconscious is a pervasive need for a logical universe that makes sense. But the real universe is always one step beyond logic.
>
> – *Frank Herbert (1965)* –

4.1 Introduction

The above quote from Frank Herbert's (1965) Dune is illustrative of one of the difficulties faced by social planners when they attempt to model or predict interactions between society's members for the purpose of drawing up policy. This challenge marks also the foundation for Hayek's (1949) argument that a system of rules is inherently ineffective if its designers assume they possess perfect knowledge about the information held by the regulated. Hayek (1988) dubbed this false belief of possessing perfect knowledge and acting upon it The Fatal Conceit. The aim of this Chapter is to provide a preliminary to the study on limitations of regulating systemic risk formation and is by no means a panacea for the problem of curtailing systemic risk.

However, rather in the spirit of The Fatal Conceit this chapter adds a caveat to the manner in which macroprudential tools' effectiveness is evaluated in current literature. In short, the assumption that regulatory tools, proposed to maintain financial stability, are independent is put to the test.[1]

In the aftermath of the Global Financial Crisis of 2007-2009 new reforms in prudential regulation have come to the fore with the aim to safeguard stability in the financial sector (Basel Committee of Banking Supervision, 2009). This study focuses on the interdependence between two such policy tools in a signaling game context: systemic risk taxation and constructive ambiguity in bailout support. Failing to account for the impact of a systemic risk tax on banks' inferences about a regulator's bailout decision leads to spurious conclusions about optimal systemic risk taxation. This result follows from banks forming and acting upon expectations about a financial regulator's inclination to bail out banks during a financial crisis.

The behavior of banks in this chapter has the flavor of the study by Farhi and Tirole (2012) in which the time-inconsistency problem of a financial regulator induces banks to coordinate with leverage choices on prospective bailout support. The main difference with their work lies in the focus of this study on the signaling role of an introduced systemic risk tax and how the set level of the tax contributes to interdependence among policy tools. With respect to endogenous policy decisions, previous studies have evaluated policy choices in light of speculative exchange rate attacks and anticipated interventions by the IMF (Drazen, 2000; Angeletos et al., 2006; Zwart, 2007).

The formation of systemic risk is driven in the model by banks' endogenous investment choices, which determine the aggregate correlation structure among banks' returns. The approach builds further on the model of Allen

[1] Acharya et al. (2012) and Freixas and Rochet (2013) discuss the merit of a systemic risk tax levied on banks as compensation for explicit or implicit financial assistance by governments in times of financial crises. A second strategy regulators can adopt to deter banks' risk-shifting behavior induced by prospective bailout support is to employ constructive ambiguity about bailout policies (Freixas, 1999; Kocherlakota and Shim, 2007; Shim, 2011).

and Gale (2000) and Acharya (2009) and is close in line with the literature on inter-bank return dependence.[2] The main extension to Allen and Gale's model is a regulator who sets a systemic risk tax for banks and faces a commitment problem in its decision to bail out distressed banks. When a substantial fraction of banks become financially distressed, the costs imposed on society of letting distressed banks fail can force the regulator to initiate bailout support.

In the presented model, banks have heterogeneous imperfect information about the conditions that force the regulator to initiate bailouts. The bailout prospects causes banks' investment choices to become strategic complements (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). As more banks become financially distressed the cost of their failure to society increases and this induces banks to believe that the regulator is likely to initiate bailout support. Preferences of banks may thereby shift towards having higher correlated returns across banks in order to trigger bailouts during banking crisis. To analyze this coordination problem faced by banks I use the global games methodology (Carlsson and van Damme, 1993; Morris and Shin, 1998, 2001). In this setting the implications of the systemic risk tax are twofold. First, an increase in the systemic risk tax may induce banks not to prefer joint correlated investments and thereby leads to lower systemic risk formation. Second, the tax has the effect of informing banks about the regulator's optimal policy and thereby shapes banks' expectations about future bailout decisions of the regulator.

Results suggest that banks' knowledge of the tax level and their private information about the regulator's inclination to initiate bailouts provide the means to infer the likelihood of receiving bailout support. In this light, a regulator that is perceived as highly inclined to initiate bailout support has

[2] Maksimovic and Zechner (1991) show that the risk characteristics of firms' cash flows are endogenously determined by aggregate investment decisions in the industry. Financially distressed industry peers impose private costs on leverage of banks and may induce risk-shifting behavior (Shleifer and Vishny, 1992). Rajan (1994) connects managerial short-termism and reputation concerns to lowering of credit policy leniency when other banks are likely to do the same. Acharya and Yorulmazer (2007) consider return dependence driven by many banks coordinating on bailout prospects.

an incentive to set a low tax in order to imitate a regulator that maintains a tough stance towards bailouts and does not need the tax to maintain financial stability, i.e. to curtail excessive risk taking by banks. Such a taxation strategy based on imitation generates the necessary uncertainty a weak regulator can exploit as constructive ambiguity. The uncertainty is driven by the observation of a low tax which does not allow banks to distinguish between these two regulator types and may thereby curtail coordination in risk taking by banks on bailout prospects. By taking the bailout policy into account I argue that in order to successfully curtail systemic risk formation with a systemic risk tax, the tax should be set independent of any future bailout policy in order to be effective.

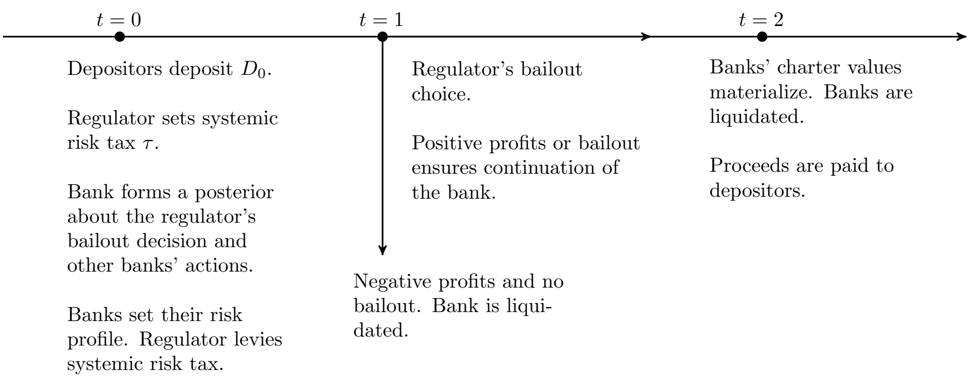
With respect to policy implications, these results suggest that significant risks are associated with systemic risk taxation when the regulator is inclined to bail out banks during crises. In order to credibly install an effective taxation policy the costs incurred by the regulator and tax payer to rescue a bank need to be high, which has proven to be the case in the wake of the 2007/2008 financial crisis. These costs are not necessarily limited to the actual absolute costs of a bank bailout, but also include the ease with which regulators and politicians can bail out banks. The effect of a higher cost associated with a bailout have the effect that the regulator can generate the necessary commitment to not bail out during a crisis if a desire exists to do so, because in such events it is less likely that banks coordinate on bailout prospects.

The Chapter is organized as follows. Section 4.2 outlines the setup of the model. Section 4.3 presents the equilibrium results and Section 4.4 provides a discussion and interpretation of results. Section 4.5 contains concluding remarks. Derivations and proofs are reserved for the appendix.

4.2 Model

The model builds upon the framework of Allen and Gale (2000) who explain financial bubbles and crises by risk-shifting behavior of a single investor in a one-period setup. I follow Acharya (2009) but extend his model with a regulator and consider many banks in order to study the formation of systemic risk based on inter-bank interactions. A financial regulator can implement a systemic risk tax in the first stage of the model and extend bailout support at the end of the first period. The presence of the second stage allows banks to derive future value from a bailout. Figure 4.1 outlines the stages of the game.

Figure 4.1. Game Tree



Banks and depositors are active in two periods that are bounded by three dates. Depositors can consume the proceeds of their deposits at the end of the game. Banks are owned and run by the same agents, they maximize their charter value over all periods and readjust strategies at the start of each period. At the end of a period, the financial regulator evaluates whether it is optimal to bail out financially distressed banks.

4.2.1 Banks and Depositors

A continuum of banks of measure 1 exists, banks are indexed by i and uniformly distributed over the unit interval. A continuum of depositors choose to supply funds for deposits at the start of each period denoted by D_t, where $t \in \{0, 1, 2\}$ indexes the dates. The amount D_t is not fixed through the periods. When a bank fails the deposits are partially destroyed, and following favorable times positive returns are reinvested. The existence of a market maker is assumed who pools all funds available for deposits in a period and channels it to the banking sector. This assumption ensures that depositors' wealth is diversified across all banks.

In a given period banks engage in perfect competition when they access the deposit market and the rate at which banks borrow funds from depositors is denoted by r_t^D. Depositors are paid at the end of a period. Furthermore, funds obtained from the deposit market constitute the only form of financing for banks. At the start of each of the two periods banks can decide on the allocation of raised deposits between *risky* assets and a *safe* asset as in the framework of Allen and Gale (2000). The appended Section 4.A.1 provides a detailed exposition of the technologies underlying the safe and risky assets.

Payoffs – Banks set strategies at $t = 0$ and if they survive the first period also at $t = 1$. At these instances banks set the proportion of deposits to be invested in the safe asset x_{it}^S and the proportion to be invested in the risky assets x_{it}^R. In addition, banks set the level of idiosyncratic volatility risk associated with the risky assets' return σ_{it}, and their choices of asset class ρ_{it}. The latter choices determine the aggregate correlation structure of returns across banks.

A bank fails at the end of a period if the return on the risky asset R_{it+1} is insufficient. That is to say, if the return on the risky asset is below r_{it+1}^c the bank will be unable to repay depositors $r_{t+1}^D D_t$. The critical return r_{it+1}^c can be inferred from the budget constraint:

$$r_{it+1}^c x_{it}^R + r_{it+1}^S x_{it}^S = r_{it+1}^D (x_{it}^R + x_{it}^S), \;\; t \in \{0, 1\}.$$

Rearranging the condition yields $r_{it+1}^c = r_{it+1}^D + (r_{it+1}^D - r_{it}^S) x_{it}^S / x_{it}^R$. If $R_{it+1} \geq r_{it+1}^c$, the pecuniary gain for the bank owners is denoted by

$$(R_{it+1} x_{it}^R + r_{it+1}^S x_{it}^S - r_{it+1}^D (x_{it}^R + x_{it}^S)) \times D_t.$$

Depositors would in this case receive a return of $r^D_{it+1}(x^R_{it} + x^S_{it})$. In the event the return on risky assets is insufficient, $R_{it+1} < r^c_{it+1}$, bank owners receive nothing and depositors receive the remaining asset value of the bank $(R_{it+1}x^R_{it} + r^S_{it+1}x^S_{it}) \times D_t$.

Furthermore, I follow Allen and Gale (2000) and introduce costs associated with investing in risky assets. These costs can arise from monitoring efforts, administration and risk management and are non-pecuniary. Banks have a parsimonious cost function $c : \mathbb{R}^+ \to \mathbb{R}^+$ which features: $c(0) = 0$; $c'(0) = 0$; $c'(x) > 0$; and $c''(x) > 0$.

Based on the previous discussions the expected payoff of bank i in a given period can be denoted by $v : [0, \sigma_{max}] \times \{\mathbb{R}^+\}^4 \to \mathbb{R}$ and is defined by

$$\begin{aligned} v(\sigma_{it}, x^R_{it}, x^S_{it}, r^D_{it+1}, r^S_{it+1}) = \int_{r^c_{it+1}}^{r_{max}(\sigma_{it})} & (R_{it+1}x^R_{it} + r^S_{it+1}x^S_{it} \\ & - r^D_{it+1}(x^R_{it} + x^S_{it}))\mathrm{d}h(\sigma_{it}, .) - c(x^R_{it}), \end{aligned} \tag{4.1}$$

where h denotes the density of the risky assets' return R_{it+1} which features mean reversion as outlined in the appended Section 4.A.1.

4.2.2 Policy and systemic risk formation

Banks face two types of risk: idiosyncratic risk and systemic risk. The idiosyncratic risk component, volatility σ_{it}, affects the probability of failure of the bank in a given period. The extend with which a bank's performance is detrimentally affected by other bank failures is denoted as systemic risk. Bank managers do not observe other banks' choices of asset classes, instead managers infer the likely aggregate action of banks through their posterior expectation about whether to receive bailout support if financially distressed. Equilibrium choices are derived by means of backward induction.

Objective of the regulator – The regulator is concerned with maintaining financial stability. To this end the regulator can bail out financially distressed banks and levy a systemic risk tax. The bailout decision is determined on the basis of whether the cost of letting a bank fail outweigh the cost of saving a bank. The cost of letting bank i fail depends on bank i's performance and the performance of all other banks, $-i$. These costs are denoted by $C(i, -i)$. The costs C feature the notion that a single bank's failure can potentially be absorbed by the banking sector, but multiple bank failures may induce failure of other banks and thus increase the costs associated with their failure (Acharya et al., 2012). The cost the regulator perceives to be associated with rescuing a bank θ are constant and are not perfectly observed by banks.[3]

The accuracy with which banks observe θ constitutes the source of the regulator's ability to exercise constructive ambiguity about its bailout decision, which is made explicit in Section 4.3. The bailout decision is denoted by $q_i \in \{0, 1\}$, where $q_i = 1$ means a bailout for bank i and $q_i = 0$ the converse. Hence, we can regard $\theta - C(i, -i)$ as the net benefit of not bailing out bank i.

The second tool of the regulator is to levy a systemic risk tax τ. The aim of such a tax is to discourage banks from taking activities that have the potential to contribute to the formation of systemic risk. In this light recent literature suggests to tax banks on the basis of a metric that proxies the costs imposed on society by the bank's failure (Acharya et al., 2012; Freixas and Rochet, 2013). To follow up on these studies, the tax is levied in this analysis on the probability of bank i facing financial distress given that at least one other bank is distressed. The tax therefore aims to discourage banks from allowing for systemic exposure to one another. However, the tax also generates costs for the regulator. These costs are measured in terms of social welfare loss due to taxation. The tax implies an implicit transfer of funds from depositors to the regulator. These funds are thereby not invested in productive activities, which constitutes a welfare cost to the regulator and are denoted by $\delta : [0, D_t] \rightarrow \mathbb{R}$ with the feature $\delta'(\tau) > 0$.

Based on the bailout decision, the benefits associated with the bailout

[3] The costs associated with rescuing a bank are not necessarily limited to the actual absolute costs of a bank bailout, but also extend to the relative ease with which regulators and politicians can bail out financial institutions. The costs can therefore also reflect the extend with which funds have already been reserved for bailout funds.

policy and the costs of the tax the following objective function of the regulator can be formulated:

$$(1 - q_i)(\theta - C(i, -i)) - \delta(\tau).$$

Furthermore, the bailout decision of the regulator follows endogenously from the notion of time inconsistency in bailout policy (O'Hara and Wayne, 1990; Brown and Dinç, 2005; Acharya and Yorulmazer, 2007). If the costs associated with letting a bank fail, C, exceed the costs of bailing out the bank, θ, the regulator will always bail out the bank. Therefore the bailout decision can be interpreted as an indicator variable; $q_i \equiv \mathbf{1}\{\theta < C(i, -i)\}$, such that the objective function can be stated as:[4]

$$\max\{0, \theta - C(i, -i)\} - \delta(\tau). \tag{4.2}$$

Based on (4.2) banks form expectations about whether a bailout will be received when financially distressed. In this light banks conjecture the probability associated with the event $\theta < C(i, -i)$ to be the probability of receiving bailout support. Increases in their portfolio weight assigned to asset classes with high correlation ρ_i result in a higher likelihood of joint failure. Consequently the probability of receiving bailout support increases as more banks opt for more weight of correlated asset classes in their portfolio. This constitutes the nature of the strategic complementarity in banks' choice of asset class ρ_i.

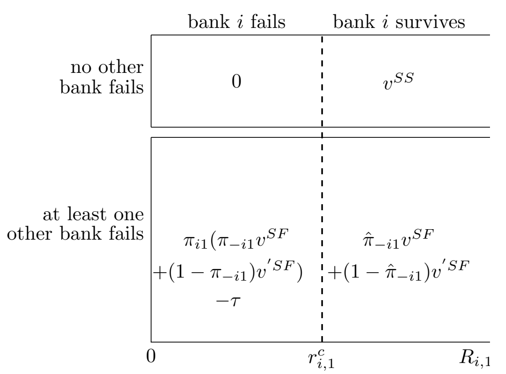
Implications for banks – A bailout event enters each bank's payoff schedule such that in the event of financial distress in the first period there exists a possibility to be allowed to operate in the second period. Likewise, other banks may receive bailout support when financially distressed and affects the payoff schedule of surviving banks.

In state SF bank i survives and at least one other bank is financially distressed. The financially distressed banks can be bailed out in this state, this occurs with probability $\hat{\pi}_{-i1}$. The payoffs associated with either action of

[4] Note that $q_i \equiv \mathbf{1}\{\theta < C(i, -i)\}$ equals 1 if $\theta < C(i, -i)$ and 0 otherwise.

the regulator are denoted by the charter value v^{SF} if a bailout is initiated, and v'^{SF} if not. we must have that $v^{SF} > v'^{SF}$, as a result of the negative spillover effect of banks' failure on surviving banks (Acharya, 2009). Turning to state FF, where the difference with SF lies in bank i being also financially distressed. In this event, the probability that i will receive a bailout is now denoted by π_{i1}, and that at least one other bank is saved is denoted by π_{-i1}. Note that the positive charter values in this state are equal to those in SF. Since if bank i would not be distressed the cost of any other bank failing would be strictly lower in comparison to the case where bank i would be distressed. This conjecture will be made explicit when banks' ex ante expectations about the costs of failure to society are defined in Section 4.3. A graphical depiction of the expected charter values for the various states and their corresponding probabilities of occurrence is presented in Figure 4.2. Furthermore, for ease of exposition if all but one bank are financially distressed, the regulator will not initiate a bailout policy.

Figure 4.2. Payoffs at the end of the first period



By allowing the three bailout probabilities (π_{i1}, π_{-i1} and $\hat{\pi}_{-i1}$) to be different, the regulator is assumed to implement bailouts for banks on a case by case basis, rather than a blanket bailout initiated for all banks. Nonetheless, the setup does not exclude the possibility of a uniform bailout across all distressed banks.

I use the notation $A_1 := \{R_{i1} \geq r^c_{i1}\}$, and $B_1 := \bigcap_{j\in[0,1]/\{i\}}\{R_{j1} \geq r^c_{j1}\}$ for ease of exposition. These terms denote respectively the events in which bank i survives, and the survival of all other banks. Likewise the complements of these events can be denoted as $A_1^c := \{R_{i1} < r_{i1}^c\}$, failure of bank i; and $B_1^c := \bigcup_{j\in[0,1]/\{i\}}\{R_{j1} < r_{j1}^c\}$, the failure of at least one other bank. The optimal strategy profile for bank i for the first period can now be denoted as

$$\begin{aligned}\sigma_{it}^*, x_{it}^{R*}, x_{it}^{S*}, \rho_i^* \in \underset{\sigma_{it}, x_{it}^R, x_{it}^S, \rho_{it}}{\arg\max} \{ & v(\sigma_{it}, x_{it}^R, x_{it}^S, r_{it+1}^D, r_{it+1}^S) \\ & + \mathbb{P}^{\mathcal{H}}(A_1 \bigcap B_1) v^{SS} \\ & + \mathbb{P}^{\mathcal{H}}(A_1 \bigcap B_1^c)(\hat{\pi}_{-i1} v^{SF} + (1-\hat{\pi}_{-i1}) v'^{SF}) \\ & + \mathbb{P}^{\mathcal{H}}(A_1^c \bigcap B_1^c)(\pi_{i1}(\pi_{-i1} v^{SF} \\ & \quad + (1-\pi_{-i1}) v'^{SF}) - \tau)\},\end{aligned} \tag{4.3}$$

where $v(.)$ is defined as (4.A.2). Note that banks incorporate their expected charter value for the second period as well in determining their strategies. The operand in (4.3) is bank i's charter value at the start of the first period and can be written conveniently as:

$$\begin{aligned}V(\sigma_{it}, \rho_i, x_{it}^R, x_{it}^S, r_{it+1}^D, r_{it+1}^S) = v(.) & + (1 - \mathbb{P}^{\mathcal{H}}(A_1^c) - \mathbb{P}^{\mathcal{H}}(B_1^c)) v^{SS} \\ & + \mathbb{P}^{\mathcal{H}}(B_1^c)(\hat{\pi}_{-i1} v^{SF} + (1-\hat{\pi}_{-i1}) v'^{SF}) \\ & + \mathbb{P}^{\mathcal{H}}(A_1^c \bigcap B_1^c)\Big(\pi_{i1}(\pi_{-i1} v^{SF} \\ & \qquad + (1-\pi_{-i1}) v'^{SF}) \\ & \qquad - (\hat{\pi}_{-i1} v^{SF} + (1-\hat{\pi}_{-i1}) v'^{SF}) \\ & \qquad - \tau\Big).\end{aligned} \tag{4.4}$$

Note that the probability that bank i and at least one other bank fail, $P^{\mathcal{H}}(A_1^c \cap B_1^c)$, is the only term in (4.4) that depends on the choice of asset class, ρ_i. Bank i will set x_{it}^{R*}, x_{it}^{S*} in a similar vein as for the second period. The key difference lies in setting σ_{it}^*, and ρ_i^*, since these affect the distribution of returns for all banks and thereby $\mathbb{P}^{\mathcal{H}}(.)$. However, ρ_i, only affects the latter term such that the optimal choice σ_{i1}^* can be expressed in terms of ρ_i^*. It is assumed that the joint event where bank i fails and at least one other bank as well is increasing in banks' contribution to the overall formation of systemic risk, namely all chosen correlation terms.

The regulator charges the bank the amount $\mathbb{P}^{\mathcal{H}}(A_1^c \bigcap B_1^c)\tau$ as systemic risk tax at $t = 0$ and after the banks set their choice of ρ_i, such that the tax is incorporated in banks' decision on the asset class.

4.3 Equilibrium analysis

In order to evaluate the equilibrium decisions of banks at the start of the first period banks' decisions with respect to their choice of asset class needs to be determined. Each bank solves in this respect:

$$\begin{aligned}
\rho^*(\pi_i) \in & \arg\max_{\rho \in [\rho^l, \rho^h]} \{\mathbb{P}^{\mathcal{H}}(A^c \bigcap B^c)(\pi_i b_i - c_i - \tau)\}, \text{ where} \\
& b_i := \pi_{-i1} v^{SF} + (1 - \pi_{-i1}) v'^{SF}; \\
& c_i := \hat{\pi}_{-i1} v^{SF} + (1 - \hat{\pi}_{-i1}) v'^{SF}.
\end{aligned}$$

Under the assumption of perfect information, each bank has knowledge with respect to the probability of receiving bailout support upon failure when at least one other bank is financially distressed. The optimal strategy for choice of asset class can then be expressed as:

$$\rho^*(\pi_i) = \rho^h \mathbf{1}\{\pi_i > (c_i + \tau)/b_i\} + \rho^l (1 - \mathbf{1}\{\pi_i > (c_i + \tau)/b_i\}). \tag{4.5}$$

In case the bailout probability π_i depends on the aggregate correlation structure, banks set $\rho^* = \rho^h$. This result is driven by the complementary nature of the choice of asset class. As more banks opt to assign more weight to the asset class prone to be correlated, the likelihood of joint failure of banks increases at the end of the first period. This reinforces banks' incentives to opt for more correlated asset classes, because as more banks fail jointly the regulator is more inclined to initiate bailout support. Hence, the strategic complementarity in choice of asset class results in multiplicity of equilibria, and implies either all banks choose ρ^h or low ρ^l (Morris and Shin, 2003).

To avoid multiplicity of equilibria as a result of strategic complementarity I consider a noisy perturbation in banks' knowledge about the cost for the regulator to initiate bailout support θ. The approach follows the global games methodology and relates closely to the works of Morris and Shin (2003), and Angeletos et al. (2006). The regulator is given the option to reveal the actual value of the bailout costs, θ, but this course of action is not optimal for the regulator. The imperfect knowledge of banks concerning θ generates the constructive ambiguity technology the regulator can exploit. The perturbation maintains strategic complementarily in banks' asset class choices but introduces additional uncertainty for banks concerning regulatory bailout policy. To explicitly incorporate constructive ambiguity endogenously, rather than assuming constructive ambiguity to be present from the outset has the advantage that signalling effects of other policy tools on this strategy can be investigated.[5] In addition to be a cost to banks, the systemic risk tax signals the type of regulator, θ, banks face.

To evaluate the signaling role of a systemic risk tax, Bayesian-Nash equilibria are considered for two cases. First, a benchmark pooling equilibrium is considered where the systemic risk tax is fixed and cannot be changed by the regulator. This approach bears similarity to the manner in which Morris and Shin (2003) solve their model on currency crises. In the second case, the regulator is allowed to change the systemic risk tax which results in a signaling game. To this end, let $\tau(\theta)$ be the systemic risk tax set by the regulator with bailout costs $\theta \in \mathbb{R}$. Furthermore, let $\rho^*(\xi_i, \tau(\theta))$ be bank i's equilibrium choice of asset class based on received signal $\xi_i \in \mathbb{R}$ about θ and observed tax τ; let $\boldsymbol{\rho}(\theta, \tau)$ be an array which contains all banks' asset class choices. Last, let $\mu(\theta < \theta' | \xi_i, \tau)$ denote bank i's posterior distribution of θ, i.e. bank i's beliefs about the regulator's type. With the posterior distribution banks infer the probability of receiving bailout support if financially distressed, $\pi_i \equiv \mu(\theta < \mathbb{E}^H(C(i, -i)) | \xi_i, \tau)$ and $\mu(\mathbb{E}^H(C(i, -i)) | \xi_i, \tau)$ for short. These

[5] Assuming constructive ambiguity to hold at all times conditions the analysis on this presumption, such that interactions between policy tools and constructive ambiguity cannot be evaluated.

expressions allow for an equilibrium definition that characterizes the main actions by banks and the regulator in the first period of the model.

Both for the case of a fixed tax and a strategic tax these equilibrium expressions are solved in the two subsequent sections.

With respect to banks' choices for $\sigma_{i0}^{*}, x_{i0}^{R*}$ and x_{i0}^{S*} at the start of the first period, these are in the same manner contingent on the banks choices for ρ_{i0} as in Acharya (2009). Since these choices do not bear consequences for the main results of this paper they are omitted.[6]

4.3.1 Fixed non-strategic systemic risk taxation

In this section the systemic risk tax is fixed, i.e. $\tau = \tau_0$. This implies $\tau^*(\theta) = \tau_0$ for all government types θ. Banks remain therefore uninformed by the systemic risk tax about the cost of bailouts. Under imperfect knowledge, banks receive a noisy signal about the regulator's cost of bailouts θ, i.e. $\xi_i = \theta + \varepsilon_i$, where $\varepsilon \sim F$ with density f and $\theta \sim G$ with density g. The signal and the prior knowledge of G allow banks to infer a posterior of θ. According to Bayes' rule the posterior distribution of θ of bank i can be expressed as:

$$\theta|\xi_i \sim \mu(\theta|\xi_i) := \frac{\int_{\theta_0}^{\theta} g(\tilde{\theta}) f(\xi_i - \tilde{\theta}) \mathrm{d}\tilde{\theta}}{\int_{\theta_0}^{\bar{\theta}} g(\theta) f(\xi_i - \theta) \mathrm{d}\theta}. \tag{4.6}$$

Banks believe they will receive a bailout if the cost of letting them fail is sufficiently high. That is, the costs of bailing out the bank are lower than some critical cost of letting the bank fail, $\theta \leq \theta^*$. A bank with signal ξ_i attaches probability $\mu(\theta^*|\xi_i)$ to the event of receiving a bailout when financially distressed, conditional on at least one other bank being financially distressed. Given this probability the optimal action of bank i is denoted by $\rho^*(\mu(\theta^*|\xi_i))$. The average action across banks can be denoted under true θ

[6] I refer the reader to proposition 2 in Acharya (2009) and the proof thereof for a detailed exposition of the choices of banks for these variables.

by

$$\int_{\xi_i \in \mathbb{R}} \rho^*(\mu(\theta^*|\xi_i))f(\xi_i - \theta)\mathrm{d}\xi_i.$$

The critical value θ^* corresponds with the ex ante expectation banks have of their cost of failure to the regulator $C(i, -i)$. Since, the outcome of $C(i, -i)$ is random, banks associate the critical level of bailout costs θ^* with $\mathbb{E}^{\mathcal{H}}(C(i, -i))$, which is increasing in banks choice of ρ_i.[7] As banks opt for asset classes prone to be correlated the joint failure probability increases and thus increases the expected cost to the regulator of letting a bank fail. For ease of exposition, I assume $\mathbb{E}^{\mathcal{H}}(C(i, -i))$ to be linearly increasing in the average of banks' asset class choices, such that the threshold condition $\theta^* = \mathbb{E}^{\mathcal{H}}(C(i, -i))$ can be stated as:

$$\theta^* = \int_{\xi_i \in \mathbb{R}} \rho^*(\mu(\theta^*|\xi_i))f(\xi_i - \theta^*)\mathrm{d}\xi_i. \tag{4.7}$$

Since the aggregate action of the banking system is decreasing in θ, we have under the critical value θ^*,

$$\int_{\xi_i \in \mathbb{R}} \rho^*(\mu(\theta^*|\xi_i))f(\xi_i - \theta)\mathrm{d}\xi_i > \theta.$$

Since f is continuous and monotonically decreasing in θ, (4.7) is a sufficient condition for the existence of a unique threshold equilibrium.

Based on (4.7) and the monotonicity of μ there exists a unique signal $\xi^* := \xi(\theta^*|\bar{\pi})$ for which a bank attaches probability $\bar{\pi}$ to the event in which bailout support is received when distressed and at least one other bank is distressed. This signal is inferred from the condition

$$\mu(\theta^*|\xi(\theta^*, \bar{\pi})) = \bar{\pi}.$$

Suppose bank i receives such a signal $\xi(\theta^*, \bar{\pi})$ and believes with probability $\bar{\pi}$ to receive bailout support when distressed and at least one other bank is

[7] The expected costs of failure follows the analogy with system wide shortfall (Acharya et al., 2012; Adrian and Brunnermeier, 2011).

distressed. In addition, suppose bank j receives signal $\xi_j < \xi(\theta^*, \bar{\pi})$. It holds that $\mu(\theta^*|\xi_j) > \bar{\pi}$. Hence, the fraction of banks with stronger beliefs about receiving bailout support when at least one other bank fails relative to bank i with belief $\bar{\pi}$ is denoted by:

$$\int_{\inf\{\Xi\}}^{\xi(\theta^*,\bar{\pi})} f(\xi_i - \theta^*)\mathrm{d}\xi_i = F(\xi(\theta^*, \bar{\pi}) - \theta^*).$$

Differentiation of this expression with respect to $\bar{\pi}$ results in the density of beliefs among banks, $\gamma(\bar{\pi}|\theta^*)$, under the true θ^*.[8] γ is the density of beliefs about receiving bailout support distributed across the banking sector for a given type of regulator θ^*. Combined with condition (4.7) and a change of variable ξ_i to $\bar{\pi}$ allows to pin down the average action of the banks with respect to their choice of asset class, ρ_i:

$$\theta^* = \int_0^1 \rho^*(\pi)\gamma(\pi_i|\theta^*)\mathrm{d}\pi_i.$$

Let $\hat{\theta} := \frac{\theta^*-\rho^l}{\rho^h-\rho^l}$ and we can state this more conveniently in terms of banks' actions:

$$\begin{aligned}\frac{\theta^* - \rho^l}{\rho^h - \rho^l} &= \frac{\int_0^1 \rho^*(\pi_i)\gamma(\pi_i|\theta^*)\mathrm{d}\pi_i - \rho^l}{\rho^h - \rho^l};\\ \hat{\theta} &= \int_0^1 \mathbf{1}\Big\{\pi > \frac{c+\tau_0}{b}\Big\}\gamma(\pi_i|\theta^*)\mathrm{d}\pi_i. \end{aligned} \tag{4.8}$$

Based on (4.5) the parameter $\hat{\theta}$ can be interpreted as an index and indicates the proportion of banks which choose ρ^h, whereas the remaining fraction chooses ρ^l.

At first it seems that (4.8) implies an increase in the systemic risk tax τ discourages banks from choosing ρ^h. The inference from this observation would be that the regulator is in a position to curtail systemic risk taxation by charging a sufficiently high systemic risk tax. However, a high systemic risk tax also poses a cost to the regulator since it reduces the investment

[8] This is possible since μ is monotonically decreasing in ξ_i.

opportunity set of depositors and bank owners. This potential reduction in wealth due to a high tax enters the regulator's objective function (4.2) through the cost δ. The result of this inference would be that the regulator can set the systemic risk tax in a manner deemed optimal.

According to (4.8) the regulator has no incentive to reveal θ to the banks in order to keep an ambiguous bailout policy. Since this would result in the perfect information case where all banks can coordinate on the prospect of receiving bailout support. In the subsequent section the systemic risk tax can be chosen freely by the regulator and in addition to being a cost to banks the tax acts as a signal that reflects the regulator's optimal policy choice with respect to bailout policy.

4.3.2 Strategic systemic risk taxation

The main result of this section is the derivation of a limited set of regulator types for which it is optimal to levy a systemic risk tax to induce banks not to coordinate on bailout prospects, i.e. not to choose ρ^h. If the costs associated with an increased dead-weight loss due to a high tax $\tau > \underline{\tau}$ exceed the net costs of letting a bank fail the regulator finds the low tax, $\underline{\tau}$, the optimal choice of systemic risk taxation. Likewise, the costs of letting banks fail can be too low to justify a higher tax due to the ensuing welfare loss. This contrasts the comparative static derived from (4.8), which seems to suggest that a high systemic risk tax results in lower systemic risk formation for any type of regulator.

Two equilibria can be identified in the setting where the regulator chooses $\tau \in [0, D_t]$. One in which banks are unresponsive to a higher systemic risk tax, a so-called pooling equilibrium; and one in which a subset of regulator types benefits from setting a higher systemic risk tax.

Proposition 4.1. (Equilibria with strategic systemic risk taxation) – *When the regulator is able to set $\tau \in [\underline{\tau}, D_t]$ (with $\underline{\tau} > 0$) two equilibria can be identified for the first period of the model, a pooling equilibrium (I.) and a semi-separating equilibrium (II.):*

I. There exists an equilibrium in which the regulator sets $\tau(\theta) = \underline{\tau}$, $\forall\theta \in \mathbb{R}$. Banks' optimal choice, and the regulator's bailout decision are respectively given by:

$$\rho^*(\xi_i, \tau) = \begin{cases} \rho^h & \text{if } \xi_i < \xi^* \\ \rho^l & \text{otherwise;} \end{cases}$$

$$q_i(\theta) = \begin{cases} 1 & \text{if } \theta < \theta^* \\ 0 & \text{otherwise.} \end{cases}$$

Where the private signal $\xi^* = \xi(\theta^*, .)$, the critical cost of initiating no bailout θ^* and index $\hat{\theta}$, in (4.8), *are the same as in section 4.3.1.*

II. When the regulator sets $\tau(\theta) \in [\underline{\tau}, \tilde{\tau}]$, with $\tilde{\tau} < D_t$ there exists an equilibrium in which

$$\tau(\theta) = \begin{cases} \tau^* & \text{if } \theta \in [\underline{\theta}, \bar{\theta}] \subset \mathbb{R} \\ \underline{\tau} & \text{if } \theta \notin [\underline{\theta}, \bar{\theta}]; \end{cases}$$

$$\rho^*(\xi_i, \tau) = \begin{cases} \rho^h & \text{if } \xi_i < -\infty \text{ or } (\xi_i, \tau) < (\xi(\underline{\theta}, .), \tau^*) \\ \rho^l & \text{otherwise;} \end{cases}$$

$$q_i(\theta) = \begin{cases} 1 & \text{if } \theta < \underline{\theta} \\ 0 & \text{otherwise.} \end{cases}$$

Where $\underline{\theta} \leq \theta^* \leq \bar{\theta}$ and $\underline{\tau} \leq \tau^* \leq \tilde{\tau} \leq D_t$. Additionally, the equilibrium values $\underline{\theta}$, and $\bar{\theta}$ solve

$$\underline{\theta} = \delta(\tau^*) = \int_{\xi_i \in \Xi} \rho^*(\mu(\bar{\theta}|\xi_i)) f(\xi_i - \bar{\theta}) d\xi_i,$$

where the last term denotes the average action across banks.

Proof. See appendix. ■

The first equilibrium *I.* denotes a pooling equilibrium in which banks' are unresponsive to the regulator's choice of τ. The optimal choice of taxation by the regulator in this case is $\underline{\tau}$, since the tax will not have an effect on bank's choices and setting it higher only results in a welfare loss. This equilibrium bears close similarity with the one derived in Section 4.3.1.

Regarding the second equilibrium, banks are responsive to the regulator's tax. It is in the interest of the regulator not to raise the tax beyond τ^*. A higher tax only results in additional costs to the regulator while banks would have already been successfully deterred in their choice for the correlated asset class ρ^h for a tax τ^*. The regulator's choice τ^* is dominated by the lower tax $\underline{\tau}$ if the net costs to bail out banks is *not* sufficiently high; or if banks' deem it likely for the regulator to initiate a bailout policy. This result is derived from the regulator's objective function (4.2) and the average action of banks with respect to their choice of ρ. Two conditions prevail that identify the types of regulator which do not prefer τ over $\underline{\tau}$:

$$\int_{\xi_i \in \Xi} \rho^*(\mu(\theta|\xi_i)) f(\xi_i - \theta) \mathrm{d}\xi_i < \delta(\tau^*); \tag{4.9a}$$

$$\theta < \delta(\tau^*). \tag{4.9b}$$

Condition 4.9a yields a $\bar{\theta}$ for which a regulator of type $\theta > \bar{\theta}$ prefers to set $\underline{\tau}$ since the costs of letting banks fail is not sufficiently high, and banks are likely to be deterred due to their private information about $\theta > \bar{\theta}$, which induces a large fraction of the banks to believe that a bailout is not a likely outcome during a crisis.

Condition (4.9b) tells us for $\theta < \underline{\theta} = \delta(\tau^*)$ the regulator will have no incentive to set τ^* since banks will not be deterred in choosing ρ^h. In this case banks private information is likely to induce a large fraction of banks to believe that $\theta < \underline{\theta}$, such that a large fraction of banks believes to receive bailout support during a crisis event. However the fact that they observe $\underline{\tau}$ for such a regulator renders banks unsure whether they face a regulator of a type $\theta < \underline{\theta}$ which is inclined to bail banks out, or a type $\theta > \bar{\theta}$ which is not inclined to do so. This ambiguity in type is the constructive ambiguity the regulator can create as a weak type by setting a tax $\underline{\tau}$ to imitate the tougher regulator. Setting any other tax between $\underline{\tau}$ and τ^* would immediately reveal that the regulator is of type $\theta < \underline{\theta}$ and would cause the banks to coordinate on bailout prospects.

4.4 Discussion of results

The main results of this paper are the regulator's limitations to set optimally a systemic risk tax for banks when the tax reveals to banks the regulator's inclination to initiate bailouts for banks. In section 4.3.1 the average action across banks in equilibrium (4.8) with respect to their choice of asset class, ρ, suggests that banks' contribution to the formation of systemic risk can be mitigated by setting a higher tax regardless of the regulator's bailout policy. This result contrasts the case where the tax is strategically set by the regulator as discussed in section 4.3.2.

Failing to account for the fact that the tax may reflect the regulator's objective to safeguard financial stability may lead to spurious conclusions about optimal systemic risk taxation. This result is driven by the regulator's objective to safeguard financial stability and renders the two policy tools interdependent. If the regulator's inclination to initiate bailout support is high, $\theta < \underline{\theta}$, a higher tax may not prove to be sufficient to alter banks' preferences for correlated assets, i.e. banks' continue to coordinate and opt for correlated assets and set ρ^h. A higher tax results in a welfare loss. This loss is driven by the distortion in investment opportunities for banks' owners and depositors.

The failure of intermediate levels of taxation, $\tau \in (\underline{\tau}, \tau^*)$, to deter systemic risk formation is due to the private information banks have with respect to the regulator's inclination to initiate bailout support. Combined with banks' private information about the regulator the observation of an intermediate tax induces banks to believe that a sufficiently high tax is apparently sub optimal for the regulator they face, because the regulator is of a type that is likely to initiate bailout support. Therefore any tax of the level $\tau \in (\underline{\tau}, \tau^*)$ that does not reflect the action of a regulator that faces relatively high costs associated with the bailout of a bank reveals to banks the regulator's type to be one that is highly inclined to bail out banks, i.e. $\theta < \underline{\theta}$.

This result implies that an intermediate tax is informative for banks and thereby cancels the effects of constructive ambiguity about bailout support to deter systemic risk formation. For regulators with a high inclination to initiate bailout support it is therefore optimal to not change the systemic risk tax in order to keep banks in the dark concerning the bailout policy. In this way the regulator with a high inclination to initiate bailout support imitates a regulator's action which is *not* inclined to initiate bailout support. The ensuing ambiguity between types drives the source of uncertainty banks face that can be exploited by the regulator as constructive ambiguity in order to lower banks' preferences for correlated assets.

Condition (4.9b) shows that the accuracy with which banks perceive the regulator's inclination to initiate bailout support has no influence on the regulator's lower threshold type $\underline{\theta}$ who is willing to set τ^*. From this we can infer that the above results are robust against changes in the specifications of the noisy perturbation. Hence, the set of regulators for which $\theta < \underline{\theta}$, the optimal taxation remains the original, or low tax $\underline{\tau}$, regardless of the distribution of private information across banks. The only requirement is that banks do not have perfect information about the regulators inclination to initiate bailout support, in order to avoid multiplicity. The upper limit of regulator types for whom it is optimal to set τ^* is increasing in the average action of banks with respect to their choice of asset class. The result is that the equilibrium value of $\underline{\theta}$ is independent renders the results in this paper not prone to the critique made by Svensson (2006) about Morris and Shin's (2002) argument that welfare can be increasing in the inaccuracy of private information.

4.5 Conclusion

The interdependence between systemic risk taxation and constructive ambiguity is relevant for their effectiveness because banks can adjust their risk profile *after* the implementation of a systemic risk tax scheme and *before* a bailout policy is executed. Banks' risk-shifting behavior results in the model from the set tax and expected bailout policy that reflect the regulator's objective to ensure financial stability. Since the level of taxation signals the regulator's stance on how to maintain financial stability, banks learn through the perceived objective of the regulator the conditions in which bailout support is likely to be initiated. I find that the introduction of a systemic risk tax therefore limits the degree of obfuscation the regulator can employ about its bailout policy for distressed banks. Conversely, if the regulator desires to maintain an ambiguous bailout policy, prospective risk shifting induced by the signaling effect of a systemic risk tax should be incorporated in the decision on the tax level. This finding suggests the existence of a trade-off between the two policy tools, and results from evaluating systemic risk taxation and ambiguous bailout programs in a joint framework.

The implications of this trade-off for macro-prudential policy inferences are two-fold. First, to evaluate the effectiveness of regulatory policy tools the policies need to be considered in a joint framework when they serve the single objective of maintaining stability of the financial industry. Failing to account for the interdependence between policy tools can lead to spurious outcomes with respect to policies' effectiveness in handling financial crises. In the context of the considered framework I find for regulators with a high inclination to initiate bailout support that the introduction of a systemic risk tax can fail to successfully deter systemic risk formation. Second, the model adds the caveat that conditioning a framework and its outcomes on the assumption that one policy tool is effective at all times may give rise to spurious results as well. To maintain constructive ambiguity imposes restrictions on the regulator's ability to set a systemic risk tax in the considered framework. If constructive ambiguity is assumed to hold at all times, the restrictions on the level of a systemic risk tax are ignored and can lead to undesired outcomes.

4.A Consequences of bank failure

4.A.1 Safe and risky assets

Safe asset – The return on the safe asset is denoted by r_t^S and materializes at the end of a period. Banks channel a proportion of their raised deposits to a sector in the economy that employs a neo-classical risk free technology. The firms in this sector and banks engage in perfect competition in accessing the market for the safe asset. This implies that r_t^S equals the marginal rate of return on capital of the risk free technology. Let $f : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ denote the production technology of the risk free asset which features $f'(x) > 0$; $f''(x) < 0$; $\lim_{x \downarrow 0} f'(x) \rightarrow \infty$; and $\lim_{x \uparrow \infty} f'(x) = 0$. In this context x denotes the total amount invested in the risk free asset. Perfect competition implies the equilibrium condition $r_t^S = f'(x)$.

Risky assets – The bank selects a risk profile based on idiosyncratic volatility risk σ_{it} and preferred asset class ρ_i. Larger values for volatility risk σ_{it} correspond with higher volatility in returns. For larger values of ρ_i the bank opts for assets with higher correlation in returns. Based on the bank's risk profile the risky assets yield a random return $R_{it+1} \sim h(\sigma_{it}, \rho_i)$, $t \in \{0, 1\}$, where the density $h(\sigma_{it}, \rho_i)$ belongs to a class of distributions $\mathcal{H}(\sigma_{it}, \rho_i, \sigma_{-it}, \rho_{-i})$ which feature mean-preserving spreads. Note that σ_{-it} and ρ_{-i} denote tuples that contain the composite actions of all other banks with respect to their choice of the risk parameters. As more banks opt for asset classes prone to be correlated, the overall performance of banks becomes more correlated. This conjecture reflects both empirical and theoretical findings in the literature on inter-bank return dependencies (Maksimovic and Zechner, 1991; Shleifer and Vishny, 1992; Rajan, 1994; Farhi and Tirole, 2012).

4.A.2 Equilibrium values at $t = 1$

The state SF is characterized by the survival of bank i and the failure of at least one bank in the first period. The optimal strategy profile of bank i is denoted by:

$$\sigma_{it}^*, x_{it}^{R*}, x_{it}^{S*} \in \underset{\sigma_{it}, x_{it}^R, x_{it}^S}{\arg\max}\, v(\sigma_{it}, x_{it}^R, x_{it}^S, r_{it+1}^D, r_{it+1}^S). \tag{4.A.1}$$

For this state v is defined by

$$v^{SF}(.) = \int_{r_{it+1}^c}^{r_{max}(\sigma_{it})} (R_{it+1}x_{it}^R + r_{it+1}^S x_{it}^S - r_{it+1}^D(x_{it}^R + x_{it}^S))\mathrm{d}h(\sigma_{it}, .) - c(x_{it}^R). \tag{4.A.2}$$

For state SS v is expressed as v^{SS}, and can be regarded as a specific case of v^{SF} in which all banks survive. A simplification is derived for v before solving for the arguments in (4.A.1). This simplification is summarized in lemma 4.1.

Lemma 4.1. *In any existing equilibrium $r_{t+1}^D = r_{t+1}^S = r_{t+1}$, i.e. the return on the safe asset is equal to the return demanded by depositors. This rate of return is equal to the critical return of banks. Hence, $r_{t+1} = r_{t+1}^D = r_{t+1}^S = r_{t+1}$.*

4.B Proofs

Proof. OF LEMMA 4.1 **(Return on deposits)**: $r_{it+1}^D = r_{it+1}^S = r_{it+1}^c$.

Suppose $r_{it+1}^D > r_{it+1}^S \geq 0$. From (4.A.2) the critical return is given by

$$r_{it+1}^c = r_{it+1}^D + (r_{it+1}^D - r_{it+1}^S)\frac{x_{it}^S}{x_{it}^R}.$$

Based on (4.A.2) and the above expression, for $r_{it+1}^D > r_{it+1}^S \geq 0$ bank i has no demand for the safe asset. However, this implies that $r_{it+1}^S = \lim_{x\downarrow 0} f'(x) \to \infty$, a contradiction.

Suppose $0 \leq r_{it+1}^D < r_{it+1}^S$. This implies that r_{it+1}^c is decreasing in x_{it}^S and (4.A.2) is increasing in x_{it}^S. Therefore, bank i has an infinite demand for the safe asset. However, for a limited supply of deposits $x_{it}^R + x_{it}^S$ the budget constraint or the short sale constraint would be violated, a contradiction. Hence, we are left to conclude that $r^D_{it+1} = r^S_{it+1} = r^c_{it+1}$. ■

Proof. OF PROPOSITION 4.1 **(Strategic systemic risk tax)**: The proofs for both equilibrium I and II are considered below.

Equilibrium I. – This equilibrium constitutes a pooling equilibrium. In this equilibrium all banks are unresponsive to the regulator's action with respect to τ. Therefore, a regulator of any type θ finds it optimal to set $\underline{\tau}$, since the welfare costs associated with the tax δ are increasing in τ. The monotonicity of δ establishes the optimality of $\underline{\tau}$.

Since the tax τ is set by all types of regulator, the tax is uninformative to banks about the regulator's type θ. Therefore, beliefs of banks about the costs of a bailout are pinned down in an equal manner as for (4.6), such that $\mu(\theta|\xi_i, \underline{\tau}) \equiv \mu(\theta|\xi_i)$. Hence, as in Section 4.3.1, banks believe under non-strategic taxation a bailout will be initiated if $\theta < \tilde{\theta}$. Additionally, as in the case with a fixed systemic risk tax the bank finds it optimal to choose ρ^h if $\xi_i < \tilde{\xi}$.

In case the regulator sets $\tau > \underline{\tau}$ banks detect a deviation. Let $\bar{\Theta}(\tau)$ denote the set of regulators for which the deviation to $\tau > \underline{\tau}$ is dominated in equilibrium. Then for any signal ξ_i we must have the following two conditions:

$$\mu(\theta \in \Theta|\xi_i, \tau) = 1,$$
$$\mu(\theta \in \bar{\Theta}|\xi_i, \tau) = 0, \text{ if } \Theta \not\subseteq \bar{\Theta}(\tau).$$

The two conditions form the natural restriction that beliefs should assign positive measure to types that could lead to signal ξ_i, and require that beliefs assign zero measure to types for which $\tau > \underline{\tau}$ is dominated in equilibrium.

The next step is to verify that the set of beliefs in equilibrium I. is non-empty for all $\tau > \underline{\tau}$. Banks react to the signal by choosing ρ^l unless they are convinced the regulator must be of a low type, i.e. if $\xi_i < -\infty$. Borrowing the conditions (4.9b) and (4.9a) from section 4.3.2 allows us to pin down the set of θ which set τ such that the strategy is dominated in equilibrium by $\underline{\tau}$. $\tilde{\theta}$ solves:

$$\tilde{\theta} = \delta(\tilde{\tau}) = \int_{\xi_i \in \Xi} \rho^*(\mu(\tilde{\theta}|\xi_i)) f(\xi_i - \tilde{\theta}) \mathrm{d}\xi_i,$$

such that $\bar{\Theta}(\tau) = \mathbb{R}$ for $\tau > \tilde{\tau}$, and $\bar{\Theta}(\tilde{\tau}) = \mathbb{R} \setminus \{\tilde{\theta}\}$. Therefore, the set of beliefs satisfying the above-mentioned conditions is non-empty for $\tau \geq \tilde{\tau}$. If $\tau \in (\underline{\tau}, \tilde{\tau})$, then the set of regulator types for which this strategy is dominated is $\Theta \setminus [\underline{\theta}, \bar{\theta}]$, where

$$\underline{\theta} = \delta(\tau) = \int_{\xi_i \in \Xi} \rho^*(\mu(\bar{\theta}|\xi_i)) f(\xi_i - \bar{\theta}) \mathrm{d}\xi_i.$$

Since $\underline{\theta} < \tilde{\theta} < \bar{\theta}$, the set of types for which τ is dominated in equilibrium is $\bar{\Theta}(\tau) = \mathbb{R} \setminus [\underline{\theta}, \bar{\theta}]$.

Equilibrium II. – In the second equilibrium, banks coordinate on the systemic risk tax. Banks take average action

$$\int_{\xi_i \in \Xi} \rho^*(\mu(\theta|\xi_i)) f(\xi_i - \theta) \mathrm{d}\xi_i$$

when $\tau < \tau^* \in [\underline{\tau}, \tilde{\tau}]$, and all banks choose ρ^l as an optimal response when $\tau \geq \tau^*$. It is optimal for the regulator to choose $\underline{\tau}$ if $\tau < \tau^*$, since for $\tau < \tau^*$ banks do not respond to the tax in which case it is optimal for the regulator to minimize welfare loss δ. Banks are responsive to the tax when $\tau > \tau^*$, such that the regulator prefers to set $\tau^* > \underline{\tau}$ in this case.

For $\theta < 0$ it is dominant for the regulator to set $\underline{\tau}$. However, when $\theta > 0$ the payoff of setting τ^* is $\theta - \delta(\tau)$, and for $\underline{\tau}$ the payoff is

$$\max \left\{ 0, \theta - \int_{\xi_i \in \Xi} \rho^*(\mu(\theta|\xi_i)) f(\xi_i - \theta) \mathrm{d}\xi_i \right\}.$$

These payoffs illustrate that the costs of setting a higher τ^* should not exceed the costs to bail out banks, and if banks deem it sufficiently likely that no bailout policy will be initiated $\underline{\tau}$ is preferred over τ^*. Based on the conditions, the regulator types which prefer τ^* over $\underline{\tau}$ have $\theta \in [\underline{\theta}, \bar{\theta}]$, where $\underline{\theta}$ and $\bar{\theta}$ solve

$$\underline{\theta} = \delta(\tau^*) = \int_{\xi_i \in \Xi} \rho^*(\mu(\bar{\theta}|\xi_i)) f(\xi_i - \bar{\theta}) \mathrm{d}\xi_i.$$

Banks' beliefs are pinned down by Bayes' rule but differ from equilibrium I, since whenever the regulator sets $\underline{\tau}$, the corresponding type $\theta \notin [\underline{\theta}, \bar{\theta}]$. Hence beliefs about a bailout policy being initiated conditional on observing $\underline{\tau}$ are

$$\mu(\theta|\xi_i, \underline{\tau}) \equiv \frac{\mu(\theta|\xi_i)}{1 - \mu(\bar{\theta}|\xi_i) + \mu(\underline{\theta}|\xi_i)},$$

where $\mu(\theta|\xi_i)$ is defined as (4.6) and $\mu(\theta|\xi_i, \underline{\tau})$ is decreasing in ξ_i. The last monotonicity result ensures uniqueness of equilibrium for the case where banks respond to a strategically set systemic risk tax. Furthermore, the fact that $\Theta \equiv \mathbb{R}$ ensures that the set of regulator types for which $\tau \in (\underline{\tau}, \tau^*)$ is dominated in equilibrium by $\underline{\tau}$ is a subset of Θ, since $\bar{\Theta}(\tau^*) = \mathbb{R} \setminus [\underline{\theta}, \bar{\theta}]$.

■

Chapter 5

Valuing Implicit Guarantees

5.1 Introduction

In the wake of Lehman Brother's collapse on September 15, 2008 a myriad of unparalleled support measures were issued for financial institutions. Many of the unanticipated actions taken by financial regulators were beyond the scope of conventional macro-prudential policy and took the form of recapitalisations, debt guarantees, asset purchases and insurances (Panetta et al., 2009). The main objective of the concerted efforts by regulators was to prevent widespread default and a credit freeze during the ensuing crisis. However, the prospect of a cornered regulator forced to implement such measures can lead to speculation about the execution of de-facto bailouts.

Safety nets can therefore give rise to moral hazard in the form of excessive risk-taking behavior by banks' managers as shown by Cordella and Yeyati (2003), and Gorton and Huang (2004).[1] Some financial institutions may thereby have derived funding advantages prior to the Global Financial Crisis. Debt issued by financial institutions deemed to receive bailout support when financially distressed are likely to borrow at more favorable terms compared to peers for whom it is not likely to receive such support.

[1] Banks may receive bailout support for reasons when deemed *too-big-to-fail*, or when *too-many* fail simultaneously (O'Hara and Wayne, 1990; Acharya and Yorulmazer, 2007; Brown and Dinç, 2011; Dam and Koetter, 2012; Farhi and Tirole, 2012). Safety-net benefits may also confer on *difficult-to-fail-and-unwind* banks (Carbo-Valverde et al., 2013).

The nature of this funding advantage can be regarded as an implicit guarantee extended by financial regulators and politicians to institutions whose survival is regarded as important to maintain financial stability. This paper aims to identify which institutions have benefited from such guarantees, to what extent, and how guarantees have been distributed among institutions.

The main contribution of this paper is the estimation procedure for implicit guarantees by considering guarantees as financial assets that can be replicated from related financial assets for which we observe prices. This has the advantage that the level of granted implicit guarantees can be freely estimated rather than imposed by the researcher. Merton's (1977; 1978) seminal model on the cost of deposit insurance is derived from the assumption that all liabilities are insured by the regulator. Duan et al. (1992) relax this stringent assumption somewhat by fixing insurance on only deposits and leave other liabilities uninsured. However, a sufficiently important institution may still receive bailout support beyond the entitled safety net support (Freixas and Rochet, 2013). If market participants belief an institution may benefit in the future from a bailout investors are likely to associate a lower risk of default relative to the situation when bailouts are not expected.

Of particular interest are the costs associated with guarantees. To infer the costs it is necessary to define the size of guarantees extended to a financial institution. The size is often set by assumption or by following the level set by a legal framework such as the deposit insurance of the Federal Deposit Insurance Corporation. By doing so the researcher may ignore rents extracted from potential future support measures, such as bailouts, that are beyond the assumption or the contemporary legal framework. Likewise, setting the guarantee by assumption may result in overestimation of extended guarantees and mispricing. In this study the maximum level of implicit guarantees is estimated from market data rather than set ex ante by assumption. The estimated maximum level of implicit guarantees is subsequently brought in relation with future bailout events to validate the implicit guarantee concept. The estimated value allows for calculating the annual rents, or the costs, associated with the implicit guarantee (Tarashev et al., 2010).

The credit risk model I propose for estimating implicit guarantees for financial institutions relies on observations on market capitalisation, credit-default-swap (CDS) spreads, and the institution's book values. I take the credit risk model of Duan and Fulop (2009) as a benchmark, but adept their model to allow for default to occur before maturity and augment the model with a price equation for CDS contracts. The addition of CDS spreads to the model serves the purpose to identify implicit guarantees extended to the institution's creditors.

The implicit guarantees are explicitly modelled through the "loss-given-default" of the financial institution. The presence of an implicit guarantee lowers the loss-given-default faced by creditors. Namely, the shortfall of the assets' value to repay debt is reduced by the guarantee. The loss-given-default marks a key component in the valuation of CDS contracts and is endogenously modelled by the assets' value of the institution and the level of implicit guarantees. Since the acquisition of CDS contracts may serve as a hedge against the default of an institution, an increase in CDS spreads can be due to increases in the probability of default or an increase in the institution's loss-given-default.

Section 5.2 presents an overview of the model. The data is subsequently described in Section 5.3. Followed by a discussion of the results in Section 5.4. Last, I conclude in Section 5.5. Derivations and proofs are reserved for the appendix.

5.2 Structural Model and Identification

5.2.1 Implicit guarantees as an asset

To extract the formation of implicit guarantees I consider a dynamic credit risk model that is based on movements in a bank's market capitalisation and CDS spreads. Specifically, I follow the seminal work of Merton (1974) and assume that the value of the bank's activities at time t, V_t, follows a geometric Brownian motion with physical drift μ_t and volatility σ:

$$\mathrm{d}V_t = \mu_t V_t \mathrm{d}t + \sigma V_t \mathrm{d}W_t, \quad t \in [t_0, T] \tag{5.1}$$

where W_t denotes a standard Brownian motion.[2]

The value of the bank's activities can not directly be observed, but can be inferred from the market capitalisation of the bank. When debt matures and no default event has arisen before maturity, equity holders repay the promised principal amount, k, to debt holders and keep any positive remainder of the bank's value as profit. The contingent claim equity holders have on the bank's activities is in this light similar to that of a barrier call option with terminal payoff[3]

$$E_T := (V_T - k)\mathbf{1}\{\min_{t_0 \leq t \leq T} V_t \geq k\}. \tag{5.2}$$

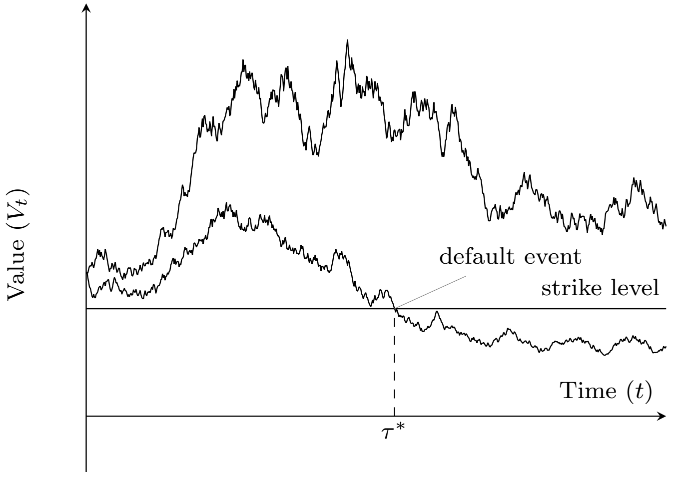
Figure 5.1 illustrates below two scenarios of the institution's value process V. In case no default event occurs until maturity, equity holders receive at maturity $V_T - k$. In case a default event occurs shareholders loose their claim and the assets of the institution are claimed by the debt holders, similar to the second generation of credit risk models (Kim, Ramaswamy, and Sundaresan, 1993; Nielsen, Saà-Requejo, and Santa-Clara, 1993; Hull and White, 1995; Longstaff and Schwartz, 1995, among others).[4]

[2] The standard Brownian motion W satisfies the usual conditions, namely $W = (W_t)$, $t \in [t_0, T]$ with respect to a reference filtration $\mathcal{F} = (\mathcal{F}_t)_{t\in[t_0,T]}$, where T denotes maturity and t indexes time. Let $\mathcal{F}_T$ denote the smallest σ-field containing $\mathcal{F}_t$ for all $t \in [t_0, T]$

[3] Note that the operator $(X)^+ := \max\{X, 0\}$.

[4] Unlike the second generation of credit risk models, in the first generation of credit risk models default occurs only at the terminal date (Merton, 1974).

Figure 5.1. Value of institution's assets and default event.



Following the notion of put-call-parity financing the terminal payoff for debt holders can be derived as:

$$\begin{aligned} D_T :&= V_T - E_T \\ &= k\mathbf{1}\{\min_{t_0 \le t \le T} V_t \ge k\} + V_T\mathbf{1}\{\min_{t_0 \le t \le T} V_t < k\}. \end{aligned}$$

The shortfall debt holders may experience at terminal time T amounts thus to $(k - V_T)^+$, the standard terminal put payoff from Merton's (1974) model.

In the event implicit guarantees have been extended to the institution with terminal payoff G_T the final payoff of debt amounts to:

$$D_T = k + (V_T - k)^+\mathbf{1}\{\min_{t_0 \le t \le T} V_t < k\} + (k - V_T)^+ + G_T.$$

Central to the implicit guarantee is that it is allowed to differ in size, i.e. the guarantee may apply to all creditors. In contrast, guarantees can also be limited to only certain types of debt classes. I consider the case where guarantees only insure against default risk and up to an unobserved maximum amount κ, which implies that the guarantees have the following payoff at maturity:

$$\begin{aligned} G_T :&= \min\{\kappa, (k - V_T)^+\} \\ &= (k - V_T)^+ - (k - \kappa - V_T)^+. \end{aligned} \tag{5.3}$$

The intuition underlying the parameter κ is that it defines the segment of the principal, k, that is insured by the guarantor. The guarantee affects the value of debt by reducing the default component in the debt payoff by the amount κ. Such that debt holders no longer face the shortfall $(k - V_T)^+$, but rather need only to hedge against the lower loss-given-default $(k - \kappa - V_T)^+$ to hedge default risk. This illustrates that the implicit guarantee decreases the loss-given-default faced by the institution's creditors, but may not necessarily imply a full guarantee. This can be interpreted as some creditors receive guarantees but not necessarily all.

Figure 5.2. Debt holder's payoff in case of default

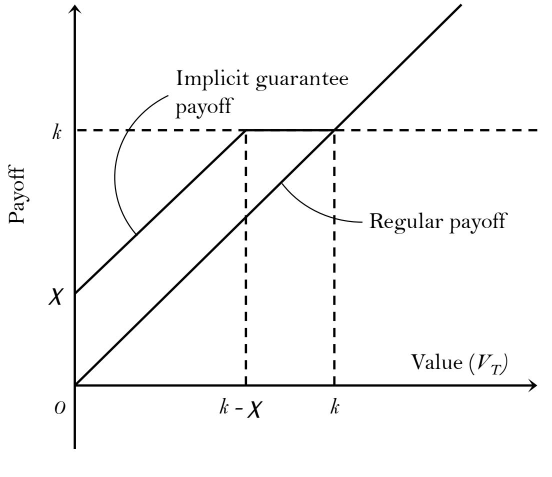


Figure 5.2 highlights the effect of an increase in the maximum level of implicit guarantees at the terminal date. The 45-degree line resembles the regular payoff in case the institution defaulted, since creditors claim the assets that generate at maturity the value V_T. The creditors of the institution face a smaller shortfall as the maximum of implicit guarantees, κ, increases, which is resembled by a shift to the left of the regular payoff schedule when

the terminal value V_T is smaller than the notional value of debt k. Note that the implicit guarantee payoff only occurs if the value of the assets is insufficient to cover the principal value of debt.

5.2.2 Identification of implicit guarantees

Since the value of equity is monotonically increasing in the value of the bank, the valuation of the equity claim (5.2) yields an implied value V_t of the institution. The market capitalisation of the institution is modelled as a barrier option that is knocked out if the default event arises, this implies that V_t is implicitly defined by (Musiela and Rutkowski, 2005):

$$\begin{aligned} E_t &:= E(V_t;\sigma,k,r,T), \\ &= E_{BS}(V_t;\sigma,k,r,T) - E_{out}(V_t;\sigma,k,r,T); \end{aligned} \tag{5.4}$$

where E_{BS} is the standard Black-Scholes call option pricing function and E_{out} the reduction in value that is due to risk of the option being knocked out, i.e. default prior to maturity:

$$\begin{aligned} E_{BS} &:= V_t\Phi(d(V_t)) - ke^{-r(T-t)}\Phi(d(V_t) - \sigma\sqrt{T-t}), \\ E_{out} &:= V_t(k/V_t)^{2(r\sigma^{-2}+1/2)}\Phi(c(V_t)) \\ &\qquad - ke^{-r(T-t)}(k/V_t)^{2(r\sigma^{-2}-1/2)}\Phi(c(V_t) - \sigma\sqrt{T-t}), \\ d(V_t) &= \frac{\ln(V_t/k) + (r+\sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}, \\ c(V_t) &= \frac{\ln(k/V_t) + (r+\sigma^2/2)(T-t)}{\sigma\sqrt{T-t}} \end{aligned}$$

The implied value V_t is subsequently used in the analysis to identify the implicit guarantees the bank received.

Based on the implicitly defined value of the institution V_t, the process (5.1) and the default event $\{V_t \leq k\}$ we are in a position to derive the spread terms of a CDS contract. In particular we are interested in the first time to default in the risk-neutral world defined as $\tau := \inf\{t \geq t_0 | V_t \leq k\}$. which is derived from the condition:

$$
\begin{aligned}
V_t &\leq k, \\
V_{t_0} \exp\{(r - \sigma^2/2)t + \sigma W_t\} &\leq k, \\
W_t &\leq \frac{1}{\sigma}(\ln(k/V_{t_0}) - (r - \sigma^2/2)t)
\end{aligned}
\tag{5.5}
$$

With the help of this default condition (5.5) we can derive the risk-neutral value of a CDS contract and derive the equilibrium spread. The CDS contract's obligee, buyer of protection, pays a fixed amount, proportional to the spread c_{t0}, continuously to the obligor, seller of protection, until the time of default or maturity. Once the default event arrives the obligor's payment $(k - \kappa - V_T)^+$ ensures that the obligee faces a limited shortfall at the time of maturity, or none at all. Note that in the derivation of Proposition 5.1 the shortfall for creditors backed by an implicit guarantee is taken into account as in (5.3).

Proposition 5.1. : CDS spread – *The combination of the default condition* (5.5) *and proposition 5.2 for the distribution of the stopping time associated with this condition yields the equilibrium credit default swap spread:*

$$
\begin{aligned}
c_{t_0} :=& c(V_{t_0}; \sigma, \kappa, k, r, T) \\
=& e^{-rT} \mathbb{E}^{\mathbb{Q}} \left[(k - \kappa - V_T)^+ \right] \frac{r/k}{P(t_0) - e^{-rT} P(T) - H(T) + H(t_0)}.
\end{aligned}
\tag{5.6}
$$

Where the survival function $P()$ and $H()$ are respectively defined by (5.A.1) *and* (5.A.2) *in Section 5.A.1. Additionally for any positive strike level k,*

$$
e^{-rT} \mathbb{E}^{\mathbb{Q}} \left[(k - V_T)^+ \right] = k e^{-rT} \Phi(\sigma\sqrt{T} - d(V_{t0})) - V_{t0} \Phi(-d(V_{t0}));
$$

the value of the expected shortfall term equals the Black-Scholes value of a put option.

Proof. For a derivation see Section 5.A.1 in the appendix ■

Result 5.1 shows that as an increase in the maximum of implicit guarantees extended decreases the loss given default faced by creditors and thereby a reduction in CDS spreads.

The value of the bank's activities (5.1), the valuation of the bank's market capitalisation (5.4) and CDS spreads (5.6) form the basis of the structural credit risk model presented below. Given the structural-form of the model, the model presented in this paper relates to the setup of second-generation credit risk models, rather than then the third generation of credit risk models which typically have a reduced-form specification (Madan and Unal, 1995; Jarrow and Turnbull, 1995; Jarrow, Lando, and Turnbull, 1997; Lando, 1998; Duffie and Singleton, 1999). In the reduced-form credit risk models the loss-given default, or recovery rate, and probability of default are generally assumed to be independent from the structural features of the firm, whereas for the purpose of inferring implicit guarantees from the recovery rate of debt we require a structural model specification.

5.2.3 Derivation of the model's likelihood function

We rewrite the continuous-time value process of the bank (5.1) into a discrete-time form, and let i index observations and let $h = \tau_i - \tau_{i-1}$ be the constant time increment between observations. The discrete-time form of the value process of the bank is then given by

$$\ln V_{\tau_i} = \ln V_{\tau_{i-1}} + \left(\mu - \frac{\sigma^2}{2}\right)h + \sigma\sqrt{h}\varepsilon_i, \quad \varepsilon_i \sim \mathrm{N}(0,1), \tag{5.7}$$

where the noise term ε_i is assumed to be independent and identically distributed (iid).

Although the value process of the bank's activities is not observed an implied value process can be inferred from the bank's market capitalisation. Assuming that equity is a residual claim of the bank's assets (5.4) allows for inferring the implied value of the bank's assets. To account for trading noise and misspecification errors a multiplicative error structure is assumed which yields the following measurement equation for the value of the bank's activities:

$$\ln E_{\tau_i} = \ln E(V_{\tau_i}; \sigma, k, r, T - \tau_i) + \delta v_i, \quad v_i \sim \mathrm{N}(0,1). \tag{5.8}$$

Note that v_i is assumed to be iid, and δ parameterises the intensity of measurement error with respect to the Black-Scholes pricing of market capitalisation.

We can regard (5.7) and (5.8) as the state-space model of Duan and Fulop (2009), where the first equation is the unobserved transition process and the second equation the measurement equation. The only exception being that Duan and Fulop consider the standard Black-Scholes call option price, whereas here we consider a barrier option.

We adopt a similar approach for the measurement equation of the bank's activities based on CDS spreads. For similar reasons as above a multiplicative error structure is assumed for this measure equation which is based on (5.6) and denoted by:

$$\ln c_{\tau_i} = \ln c(V_{\tau_i}; \sigma, k, \kappa, r, T) + \varsigma u_i, \quad u_i \sim \mathrm{N}(0,1); \tag{5.9}$$

where u_i is iid. In short, the measurement equation (5.8) based on market capitalisation identifies the unobserved value of the bank's activities, and the measurement equation (5.9) then allows for identifying the maximum of implicit guarantees extended. The issue of misspecification and credit-risk counter party risk is evaluated subsequently in the section on results, Section 5.4.

The noise structure imposed on the CDS-spread based measurement equation (5.9) serves the purpose to control for omitted country-party credit risk as well misspecification error. Counter-party credit risk may also be priced in the CDS spreads as found by Arora et al. (2012). Although the proportional noise structure is no panacea to the latter problem, we can expect that if counterpart credit risk is prevalent it is likely to influence the volatility parameters of the noise structure, δ and ς. In Section 5.4 a robustness test is performed to infer to what extend these parameter estimates are driven by counter-party credit risk characteristics.The latter argument may as well hold for the equity-based measurement equation (5.8)

We are now in a position to extend the credit risk model of Duan and Fulop (2009) with (5.6) to construct a state-space model that allows for the estimation of limited guarantees on debt as perceived by the market. The ensuing state-space model is a system of equations formed by the transition process (5.7), the measurement equation (5.8), and (5.9). The model contains five parameters denoted by $\boldsymbol{\theta} = [\mu, \sigma, \delta, \varsigma, \kappa]$.

Let the sample of market capitalisation values up to the i^{th} observation be denoted by $\mathcal{E}_i := \{E_{\tau_j} : j \in \{0, ..., i\}\}$, and similarly for the observed CDS spreads by $\mathcal{Y}_i := \{c_{\tau_j} : j \in \{0, ..., i\}\}$. The functional form of the state-space model associated with (5.7) - (5.9) can in principle be stated for n observations as:

$$f(\mathcal{E}_n, \mathcal{Y}_n|\boldsymbol{\theta}) = f(E_{\tau_n}, c_{\tau_n}|\mathcal{E}_{n-1}, \mathcal{Y}_{n-1}, \boldsymbol{\theta}) \dots f(E_{\tau_1}, c_{\tau_1}|\mathcal{E}_0, \mathcal{Y}_0, \boldsymbol{\theta}). \tag{5.10}$$

To estimate (5.10) we simplify matters by estimating the expected values of each term on the right-hand side of the likelihood separately in a sequential order. The first step is to take a likelihood contribution term and express it as:

$$\begin{aligned} &f(E_{\tau_i}, c_{\tau_i}|\mathcal{E}_{i-1}, \mathcal{Y}_{i-1}, \boldsymbol{\theta}) \\ &\qquad = \int_0^\infty f(E_{\tau_i}, c_{\tau_i}|V_{\tau_{i-1}}, \boldsymbol{\theta}) g(V_{\tau_i}|\mathcal{E}_{i-1}, \mathcal{Y}_{i-1}, \boldsymbol{\theta}) \mathrm{d}V_{\tau_{i-1}}, \end{aligned} \tag{5.11}$$

where g denotes the prediction density of V_{τ_i} based on previously observed data. The error structure in the equity-based measurement equation (5.8) complicates matters, if this error structure is not assumed the model specification would bear close resemblance to Duan (1994, 2000). However in order to maximise the likelihood function, (5.10), in the presence of an error structure associated with measurement, the filtering estimation procedure proposed by Pitt and Shephard (1999) and Pitt (2002) is adopted. An outline of the procedure is presented in the appended Section 5.A.2.

5.3 Data

The sample of 150 financial institutions comprises of daily market capitalization values and daily observed CDS spread quotations that cover the period January 2004 through July 2007. The equity data is obtained from Thompson Reuter's Datastream and the CDS spreads have been provided by the Markit Group. The main motivation for the sample period lies in the observation that prior to 2004 the data on CDS spreads showed sequences of missing observations and July 2007 marks the first time concerted efforts by financial market regulators were taken to stabilise the financial system.[5] In the period that followed until 2009, denoted as the Global Financial Crisis, a myriad of unparreled support measures were issued for financial institutions. The aim of the analysis is to evaluate whether there exist a statistical link between implicit guarantees estimated for the period January 2004 through July 2007 and to see if they relate to future bail out events, that can be interpreted as the materialization of the guarantees perceived by investors, and acts at the same time as a model validation exercise. In addition to the market data, balance sheet data is required as a proxy for the strike level that triggers default, denoted as k above.

The time to maturity, T, is set throughout to 5 years. Motivation for this choice is based on the observation that CDS contracts with a maturity of five years are traded more frequent and are more liquid (BBA, 2006). The idea is to mitigate the interference of trading noise stemming from an illiquid market in the estimation of the model's parameters. To some extend the proportional noise structure also controls for this as argued by Duan and Fulop (2009). Corresponding to a maturity of five years, the risk-free is the 5-year Treasury constant maturity rate obtained from the U.S. Federal Reserve.

[5] The ECB allowed for low-interest rate credit lines in the amount of USD 130 billion on August 9, 2007. The Federal Reserve subsequently issued temporary reserves in the amount of USD 12 billion.

5.4 Empirical analysis

5.4.1 Descriptives

Table 5.1 reports parameter estimates of the top 30 financial institutions in terms of the estimated proportion of liabilities being implicitly guaranteed and which received bailout support during the Global Financial Crisis. The columns contain the maximum likelihood estimates of the presented credit risk model's parameters, (5.7)–(5.9), with their asymptotic standard errors in brackets. The estimated asset volatility parameters, σ are stated per annum and are in line with what may be expected of their values. Their standard errors are generally very small, unlike the standard errors of the drift parameter, μ, which are characterised by a substantial amount of sampling errors. These results are so far in line with expectations.

The estimated values for the guarantee parameter, κ, can be interpreted as a percentage of the face value of the institutions liabilities that is implicitly guaranteed. That is to say for the case of US Bancorp, ranked first, that 29.1 percent of its face value is perceived by the market to be implicitly guaranteed. The test results presented in the last column relate to the likelihood ratio test whether implicit guarantees are present. Only in a few cases does the data suggest the presence of implicit guarantees. When we take a significance level of 10 percent we find that implicit guarantees have likely accrued to 9 institutions that actually received bailout support. Notably among these cases are AIG, Bank of America, Danske Bank, Fannie Mae, Freddie Mac, JP Morgan Chase and US Bancorp.The reason for this limited number of institutions is driven by the inclusion of the noise term and associated relevance parameter ς in the measurement of CDS spreads in (5.9). Results for the case where ς to zero, not reported, generally result in a larger number of institutions for which likelihood ratio test indicates that implicit guarantees are likely to be present.

Summary statistics for the credit risk model's parameter estimates are presented in Table 5.2 for all of the 150 sampled financial institutions. There are no notable differences between the estimated values for the per annum

Table 5.1. **Model estimation results for 30 bailed out financial institutions**

	Parameter Estimates										LR test
	Credit risk model parameters						Model noise parameters				
Institution's name	σ		μ		κ		$\delta \times 100$		ς		*p value*
US Bancorp	0.199	[0.012]	-0.024	[0.214]	0.291	[0.152]	0.349	[0.140]	0.576	[0.557]	0.032
Danske Bank	0.070	[0.005]	0.002	[0.156]	0.209	[0.115]	0.297	[0.177]	0.659	[0.603]	0.037
JP Morgan Chase	0.086	[0.003]	0.007	[0.127]	0.203	[0.117]	0.292	[0.103]	0.479	[0.515]	0.048
Freddie Mac	0.067	[0.012]	0.000	[0.220]	0.193	[0.117]	0.399	[0.149]	0.467	[0.486]	0.043
Capital One	0.151	[0.010]	-0.556	[0.093]	0.178	[0.121]	0.800	[0.227]	0.396	[0.476]	0.078
Fannie Mae	0.064	[0.042]	-0.004	[0.137]	0.172	[0.071]	0.320	[0.180]	0.359	[0.597]	0.042
Nordea Bank	0.064	[0.006]	-0.026	[0.068]	0.170	[0.102]	0.211	[0.163]	0.413	[0.543]	0.075
Citigroup	0.076	[0.005]	0.015	[0.250]	0.137	[0.111]	0.273	[0.084]	0.627	[0.530]	0.115
ABN Amro	0.095	[0.009]	-0.875	[0.147]	0.127	[0.093]	0.348	[0.277]	0.612	[0.472]	0.174
Bank of America	0.060	[0.009]	0.037	[0.100]	0.106	[0.032]	0.226	[0.187]	0.516	[0.532]	0.046
AIG	0.223	[0.006]	-0.183	[0.104]	0.095	[0.024]	0.271	[0.225]	0.524	[0.592]	0.031
American Express	0.142	[0.008]	0.086	[0.100]	0.093	[0.071]	0.404	[0.148]	0.432	[0.619]	0.192
BNP	0.058	[0.010]	-0.067	[0.139]	0.089	[0.077]	0.377	[0.217]	0.642	[0.541]	0.134
Societe Generale	0.076	[0.009]	-0.064	[0.222]	0.083	[0.076]	0.282	[0.280]	0.447	[0.607]	0.141
UBS	0.058	[0.012]	-0.092	[0.122]	0.078	[0.065]	0.233	[0.074]	0.565	[0.487]	0.171
Goldman Sachs	0.061	[0.016]	0.114	[0.121]	0.071	[0.065]	0.323	[0.346]	0.513	[0.578]	0.156
Credit Agricole	0.050	[0.017]	-0.031	[0.110]	0.060	[0.054]	0.278	[0.100]	0.539	[0.608]	0.176
RBS	0.049	[0.017]	-0.236	[0.150]	0.054	[0.062]	0.311	[0.193]	0.514	[0.515]	0.153
Bank of Ireland	0.098	[0.009]	0.077	[0.198]	0.040	[0.069]	0.355	[0.245]	0.632	[0.551]	0.222
Morgan Stanley	0.053	[0.019]	0.083	[0.222]	0.035	[0.059]	0.509	[0.160]	0.617	[0.522]	0.185
ING Group	0.045	[0.018]	-0.072	[0.180]	0.030	[0.069]	0.265	[0.097]	0.409	[0.581]	0.191
Natixis	0.059	[0.020]	0.050	[0.066]	0.017	[0.105]	0.360	[0.174]	0.386	[0.461]	0.151
Banca Monte dei Paschi	0.050	[0.015]	0.057	[0.145]	0.014	[0.019]	0.214	[0.095]	0.645	[0.564]	0.193
KBC Group	0.072	[0.014]	-0.299	[0.175]	0.000	[0.089]	0.284	[0.171]	0.535	[0.480]	0.392
Northern Rock	0.075	[0.016]	-0.416	[0.204]	0.000	[0.054]	0.127	[0.182]	0.568	[0.541]	0.303
Anglo Irish Bank Corp	0.168	[0.007]	-0.171	[0.135]	0.000	[0.075]	0.159	[0.068]	0.600	[0.424]	0.369
IKB	0.295	[0.006]	-0.578	[0.090]	0.000	[0.135]	0.488	[0.172]	0.438	[0.488]	0.323
EFG Euro Bank	0.162	[0.015]	0.064	[0.211]	0.000	[0.094]	0.731	[0.269]	0.473	[0.406]	0.396
Suntrust Banks	0.096	[0.013]	-0.261	[0.074]	0.000	[0.082]	0.575	[0.260]	0.435	[0.519]	0.374
Allied Irish Bank	0.083	[0.021]	-0.033	[0.147]	0.000	[0.079]	0.343	[0.254]	0.561	[0.541]	0.312

Notes: Table reports parameter estimates of the credit risk model, (5.7)–(5.9), with associated standard errors presented in brackets. 30 financial institutions are ranked in descending order by the estimated value for the guarantee parameter κ. Estimates and standard errors associated with the noise parameter δ are multiplied by 100. The final column reports test results of a model likelihood ratio test, where under the null no implicit guarantees exist, $\kappa = 0$, and the alternative suggests the existence of a level of implicit guarantees, $\kappa \in (0, 1)$.

volatility and drift parameters. Combined with the presented values in Table 5.1 it can be noted that the estimated value for implicit guarantee parameter κ is higher for institutions that received bailout support during the Global Financial Crisis. In the subsequent section a validation exercise is provided to test this proposition more formally.

Table 5.2. **Summary statistics parameter estimates**

Parameter	*mean*	*std. dev.*	*min*	*p25*	*median*	*p75*	*max*
σ	0.2453	0.2115	0.0440	0.0765	0.1638	0.3460	0.9797
μ	0.0567	0.2739	-0.8752	-0.0350	0.0490	0.1435	1.2919
κ	0.1065	0.1509	0.0000	0.0000	0.0413	0.1709	0.2914
$\delta \times 100$	0.7056	0.7678	0.1242	0.3202	0.4495	0.6914	4.7114
ς	0.5361	0.0988	0.3093	0.4646	0.5386	0.6121	0.7777

Notes: Table reports descriptive statistics for the 150 sampled financial institutions. σ denotes the per annum volatility of the market value of the institution's assets; μ the drift term per annum of the market value of assets; κ the proportion of the face value of the institution's liabilities that is implicitly guaranteed to be repaid. The noise parameters δ and ς correspond respectively to the model equations (5.8) and (5.9). Note that the estimated values of δ have been multiplied by 100.

The estimated values for the noise parameter δ are in line with the values found by Duan and Fulop (2009). Since the considered credit-risk model features a similar stylised structure as the Merton (1974) model we can interpret the values estimated for δ parameter as the magnitude of measurement error stemming from misspecification. Duan and Fulop (2009) ask a similar question and perform a cross-sectional regression analysis to ascertain whether the estimated values for δ are in line with commonly prior adopted proxies for market liquidity. Their findings give rise to the notion that higher estimated values for δ is actually trading noise rather than measurement error. They find that δ estimates are positively influenced by a growing bid-ask spread and for larger firms they find lower estimated values of δ.

5.4.2 Validation of implicit guarantees

Table 5.3. **Validation of implicit guarantees**

Bailout received during the Global Financial Crisis

	(1)	(2)	(3)
$\hat{\kappa}$	2.625**		2.439**
	[1.066]		[1.012]
ln(Total Assets)		0.095***	0.084***
		[0.024]	[0.031]
Observations	150	150	150
log-likelihood	-80.453	-73.512	-72.850
Pseudo R^2	0.253	0.223	0.261

Notes: Table reports the marginal effect of variables derived from logit regressions for whether an institution received financial support or guarantees from central regulators during the Global Financial Crisis. $\hat{\kappa}$ stands for the estimated proportion of the face value of the firm's liabilities that is implicitly guaranteed to be repaid in full. The regressors are obtained in the pre-crisis period. Standard errors are robust against heteroskedasticity. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level.

Table 5.3 presents in a similar manner to Chapter 2 the results of a validation test for the implicit guarantee estimate of the proportion of the face value of a firm's liabilities that is implicitly guaranteed to be repaid. While controlling for size, to account for the too-big-to-fail hypothesis, we find a stable marginal effect of a one percentage point increase in the implicit guarantee estimate results in a 2.4 percentage point increase in the probability of receiving bailout support during a future crisis. The marginal effect of the size variable the logarithm of total assets bears similarity to the result found in Chapter 3.

The merit of this validation test lies in the cross-sectional analysis of implicit guarantee estimates. Even though table 5.1 seems to suggest that the measure captures the concept of implicit guarantees, since we find here estimates that differ significantly from zero in a statistical sense, it may still be the case that the measure picks up measurement or misspecification error. To some extent the proportional noise term may account for measurement error. These errors may for instance arise from the model specification which contains the assumption that maturities and default risks are equal across liabilities. This shortcoming motivates the validation of the guarantee estimates in the cross-section to test if the measurement error is sufficiently random .

5.5 Concluding Remarks

This Chapter presents an adaptation and extension of the credit risk model by Merton (1974). The main difference lies in the possibility of default to occur maturity and the inclusion of a pricing scheme for CDS contracts that allows for determining the spreads of such a contract. The recovery rate of the firm's liabilities is assumed to be determined by the shortfall the firm is likely to face at maturity and is therefore time-varying rather than constant. Additionally, creditors may benefit from so-called implicit guarantees that materialize when the firm is facing a shortfall at maturity and the financial regulators deem it optimal to bail out the firm's creditors to keep the business afloat.

Despite the result that we only find a handful of firms that seem to have benefitted from implicit guarantees by obtaining a few estimates of implicit guarantees which are significantly differ from zero, a cross-sectional validation study indicates that the guarantee estimates pertain to future bailouts in a significant manner.

5.A Derivations

5.A.1 Terms of the Credit Default Swap

In this section the derivation of the no-arbitrage spreads of the CDS contract is presented. In what follows we require a standard Brownian motion W that satisfies the usual conditions, namely $W = (W_t)$, $t \in [t_0, T]$ with respect to a reference filtration $\mathcal{F} = (\mathcal{F}_t)_{t\in[t_0,T]}$, where T denotes maturity and t indexes time. Let $\mathcal{F}_T$ denote the smallest sigma field containing $\mathcal{F}_t$ for all $t \in [t_0, T]$. Additionally, a survival function of the underlying reference institution is required to value the cash flows associated with the CDS contract.

The following proposition is useful to obtain the distribution of the default time.

Proposition 5.2. *Let the random variable $Y_t := y_0 + \nu t + \sigma W_t$, where $\nu \in \mathbb{R}$, y_0, $\sigma > 0$, and W_t is a standard Brownian motion under $\mathbb{P}$. Then the random variable $\tau := \inf\{t \geq t_0 | Y_t = 0\}$ has an inverse Gaussian probability distribution under $\mathbb{P}$, that is for a default time s:*

$$\mathbb{P}\{\tau \geq s\} = \Phi\Big(\frac{y_0 + \nu s}{\sigma\sqrt{s}}\Big) - e^{-2\nu\sigma^{-2}y_0}\Phi\Big(\frac{-y_0 + \nu s}{\sigma\sqrt{s}}\Big),$$

where Φ denotes the standard normal cumulative distribution function.

Proof. For a derivation see Section A.18. in Musiela and Rutkowski (2005) ■

Substituting the condition (5.5) for $Y_t = 0$ in proposition 5.2 implies, under risk-neutral valuation, $\nu = r - \sigma^2/2$, and $y_0 = -\ln k/V_{t_0}$ and yields the probability function of no default up and until time s:

$$\begin{aligned} P(s) =& \Phi\Big(\frac{-\ln k/V_{t_0} + (r - \sigma^2/2)s}{\sigma\sqrt{s}}\Big) \\ & - \exp\{2(r + \sigma^2/2)\sigma^{-2}\ln(k/V_{t_0})\} \\ & \quad \times \Phi\Big(\frac{\ln k/V_{t_0} + (r - \sigma^2/2)s}{\sigma\sqrt{s}}\Big). \end{aligned} \tag{5.A.1}$$

Differentiating this survival function with respect to s and negating then yields the probability density function of the time of default:

$$f(s) := -\frac{\mathrm{d}P(s)}{\mathrm{d}s} = \frac{-\ln(k/V_{t_0})}{2\sigma s\sqrt{s}}\phi\Big(\frac{-\ln(k/V_{t_0}) + (r+\sigma^2/2)s}{\sigma\sqrt{s}}\Big),$$

where ϕ denotes the standard normal density function.

The CDS contract's obligee, buyer of protection, pays a fixed amount c continuously to the obligor, seller of protection, until the time of default or maturity. Once the default event arrives the obligor's payment ensures that the obligee faces no shortfall at the time of maturity. This payment therefore amounts to the equivalent amount at maturity of

$$\frac{(k-V_t)^+}{k}\mathbf{1}\{\min_{t_0\le s\le T} V_s \le k\} = \frac{(k-V_t)^+}{k}.$$

The value of this claim amounts to a down-and-in put-barrier option and equals the payoff of an European put option.

The discounted risk-neutral value of the stream of payments c the obligee pays amounts to

$$\begin{aligned} c\int_{t_0}^{T} e^{-rs}P(s)\mathrm{d}s &= \frac{c}{r}\Big(P(t_0) - e^{-rT}P(T)\Big) - \frac{c}{r}\int_{t_0}^{T} e^{-rs}f(s)\mathrm{d}s \\ &= \frac{c}{r}\Big(P(t_0) - e^{-rT}P(T)\Big) - \Big(H(T) - H(t_0)\Big), \end{aligned}$$

where

$$\begin{aligned} H(s) :=& \exp\{2(r-\sigma^2/2)\sigma^{-2}\ln(k/V_{t_0})\} \\ &\times \Big(\Phi\Big(\frac{\ln(k/V_{t_0}) + (r-\sigma^2/2)s}{\sigma\sqrt{s}}\Big) \\ &- \Phi\Big(\frac{-\ln(k/V_{t_0}) + (r-\sigma^2/2)s}{\sigma\sqrt{s}}\Big)\Big). \end{aligned} \tag{5.A.2}$$

The value of the the CDS contract equals zero, which implies that values of the expected cash flows of both parties cancel each other in the risk-neutral world:

$$c\int_{t_0}^{T} e^{-rs}P(s)\mathrm{d}s = e^{-rT}\mathbb{E}^{\mathbb{Q}}\big((V_t-k)^+\big)\,k.$$

Solving for the spread c then yields an equilibrium solution for CDS spreads at time t_0:

$$c_{t_0} = \mathbb{E}^{\mathbb{Q}}\big((k-V_t)^+\big)\frac{r}{ke^{rT}}\frac{1}{P(t_0)-e^{-rT}P(T)-H(T)+H(t_0)}.$$

5.A.2 Maximum likelihood estimation with a particle filter

To deal with the potential problem of encountering measurement errors in inferring the implied value of the bank's activities we introduce an adaptation of the expression for the likelihood contribution (5.11) above. This adaption allows us to to evaluate the likelihood function numerically. Note that below we make use of the short-hand expression

$$\hat{V}(E_{\tau_i}, v_i) := E^{-1}(E_{\tau_i}\mathrm{e}^{-\delta v_i};\sigma,k,r,T-\tau_i),$$

which is the inversion of (5.8). In addition, we require the derivative of this measurement equation with respect to market capitalisation E_t, which is equivalent to :

$$\Psi(E_{\tau_i}, v_i, k, r, T-\tau_i|\boldsymbol{\theta}) := \frac{\partial E(\hat{V}(E_{\tau_i}, v_i);\sigma,k,r,T-\tau_i)}{\partial V_t}.$$

Since measurement errors are considered to be independent from the value of a bank's activities the first term in the integrand of the likelihood contribution (5.11) can be stated as:

$$\begin{aligned}
&f(E_{\tau_i}, c_{\tau_i}|V_{\tau_{i-1}},\boldsymbol{\theta})\\
&\quad= \int_{-\infty}^{\infty} f(E_{\tau_i}, y_{\tau_i}|v_i, V_{\tau_{i-1}},\boldsymbol{\theta})\phi(v_i|\boldsymbol{\theta})\mathrm{d}v_i\\
&\quad= \int_{-\infty}^{\infty} \frac{f(V_{\tau_i}=\hat{V}(E_{\tau_i}, v_i), c_{\tau_i}|v_i, V_{\tau_{i-1}},\boldsymbol{\theta})}{\Psi(E_{\tau_i}, v_i, k, r, T-\tau_i|\boldsymbol{\theta})\mathrm{e}^{\delta v_i}}\phi(v_i|\boldsymbol{\theta})\mathrm{d}v_i \qquad (5.A.3)
\end{aligned}$$

Note that Theorem 2.2 from Duan (1994) is used to rewrite (5.A.3). Taking both (5.11) and (5.A.3) allows for a convenient expression of the i^{th} likelihood contribution:

$$\begin{aligned}
&f(E_{\tau_i}, c_{\tau_i} | \mathcal{E}_{i-1}, \mathcal{Y}_{i-1}, \boldsymbol{\theta}) \\
&\quad = \int_0^\infty \int_{-\infty}^\infty \frac{f(V_{\tau_i} = \hat{V}(E_{\tau_i}, v_i), c_{\tau_i} | v_i, V_{\tau_{i-1}}, \boldsymbol{\theta})}{\Psi(E_{\tau_i}, v_i, k, r, T - \tau_i | \boldsymbol{\theta}) \mathrm{e}^{\delta v_i}} \\
&\qquad \times \phi(v_i | \boldsymbol{\theta}) g(V_{\tau_i} | \mathcal{E}_{i-1}, \mathcal{Y}_{i-1}, \boldsymbol{\theta}) \mathrm{d}v_i \mathrm{d}V_{\tau_i} \\
&\quad = \mathbb{E}\left[\left. \frac{f(V_{\tau_i} = \hat{V}(E_{\tau_i}, v_i), c_{\tau_i} | v_i, V_{\tau_{i-1}}, \boldsymbol{\theta})}{\Psi(E_{\tau_i}, v_i, k, r, T - \tau_i | \boldsymbol{\theta}) \mathrm{e}^{\delta v_i}} \right| \mathcal{E}_{i-1}, \mathcal{Y}_{i-1} \right] \\
&\quad = \mathbb{E}\left[\left. \frac{f(V_{\tau_i} = \hat{V}(E_{\tau_i}, v_i), c_{\tau_i} | v_i, V_{\tau_{i-1}}, \boldsymbol{\theta})}{\Psi(E_{\tau_i}, v_i, k, r, T - \tau_i | \boldsymbol{\theta}) \mathrm{e}^{\delta v_i}} \right| E_{\tau_{i-1}}, c_{\tau_{i-1}} \right]
\end{aligned} \tag{5.A.4}$$

The first step towards the second equality in (5.A.4) is to express the likelihood contribution in terms of the expectation of both measurement error and the value of the bank's activities. The last expression is a simplification, since the expectation only needs to be conditioned on the preceding values of market capitalisation and the CDS spread.

The above expression can be estimated by the approach proposed by Pitt and Shephard (1999), Pitt (2002) to deal with measurement error in a state-space model's measurement equation. This estimation procedure is rooted on the work of Gordon et al. (1993) and Doucet et al. (2001) on the applications of particle filtering. Estimation of the contributions to the likelihood function are carried out sequentially for all terms in (5.10).

The particle filter initiates with the assumption $V_{\tau_0}^{(m)} = \hat{V}(E_{\tau_i}, 0)$ for all m, where m indexes the M replications of the filtering procedure. For subsequent observations we adopt the following three-step procedure (Duan and Fulop, 2009):

- **Step 1:** Start with $V_{\tau_i}^{(m)}$ in the equal-weight filtering sample. For $i = 1$ this translates in the use of the initially set $V_{\tau_0}^{(m)}$. Take a pre-sampled standard normal value $v_{i+1}^{(m)}$ and calculate $V_{\tau_{i+1}}^{(m)} = \hat{V}(E_{\tau_i}, v_i^{(m)})$. This procedure results in M pairs $\{V_{\tau_{i+1}}^{(m)}, V_{\tau_i}^{(m)}\}$.

- **Step 2:** Calculate the importance weight associated with the pair $\{V_{\tau_{i+1}}^{(m)}, V_{\tau_i}^{(m)}\}$:

$$w_{i+1}^{m} = \frac{f(\hat{V}_{\tau_{i+1}}^{(m)} | V_{\tau_i}^{(m)}, \boldsymbol{\theta})}{\Psi(E_{\tau_i}, v_i, k, r, T - \tau_i | \boldsymbol{\theta})}.$$

  Assign $\pi_{i+1}^{(m)} = w_{i+1}^{m} / \sum_{m=1}^{M} w_{i+1}^{m}$ to the value $\hat{V}_{\tau_{i+1}}^{(m)}$. Note that from (5.7) we arrive at

$$f(\hat{V}_{\tau_{i+1}}^{(m)} | V_{\tau_i}^{(m)}, \boldsymbol{\theta}) = \frac{1}{V_{\tau_i}^{(m)} \sigma \sqrt{h}} \phi\Big(\frac{\ln(V_{\tau_{i+1}}^{(m)} / V_{\tau_i}^{(m)}) - (\mu - \sigma^2/2)h}{\sigma \sqrt{h}} \Big).$$

- **Step 3:** Construct an empirical distribution with the weighted sample $\{V_{\tau_{i+1}}^{(m)}, \pi_{i+1}^{(m)}\}$ for all m. Use this empirical distribution to resample M new candidate lagged values in order to filter the next observation.

As found by Pitt (2002), the importance weight in Step 2 is the term inside the expectation operator of (5.A.4). This conditional likelihood can now be approximated for a given set of parameters $\boldsymbol{\theta}$ by

$$\hat{f}(E_{\tau_{i+1}}, c_{\tau_{i+1}} | \mathcal{E}_{i-1}, \mathcal{Y}_{i-1}, \boldsymbol{\theta}) = \frac{1}{M} \sum_{m=1}^{M} w_{i+1}^{m}.$$

This procedure allows us to estimate sequentially the contribution (5.11) for each observation such that we can estimate the likelihood function (5.10), and derive the optimal maximum likelihood estimates of $\boldsymbol{\theta}$.

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Samenvatting

Dit proefschrift is een bundeling van vier studies op het gebied van de formatie van systeem risico in de financiële sector. Hoofstukken 2 en 3 bevatten de beschrijving, opzet en resultaten van twee empirische studies. De laatste twee hoofdstukken 4 en 5 beschrijven twee theoretische modellen waarbij het laatste model in hoofdstuk 5 wordt geschat met behulp van gegevens over de krediet posities van banken. Naast de bijdragen op het gebied van de formatie van systeem risico bevat dit proefschrift ook bijdragen op het gebied van het modelleren van krediet risico met behulp van premies voor het financiële derivaat Credit Default Swap (CDS). Een contract waarvoor een periodieke betaling van een premie verzeker biedt tegen het faillissement van een instantie.

De Globale Financiële Crisis werd in augustus 2007 ingeluid met de georganiseerde interventies van verscheidene centrale banken in de banken sector. Sindsdien is het concept *systeem risico* onderwerp van discussie in academische kringen, onder beleidsmakers, maar heeft ook de aandacht gekregen van het algemeen publiek. De formatie van systeem risico kan worden beschouwd als een toename van risico's die bijdragen aan de waarschijnlijkheid en kosten die gemoeid zijn met substantiële schade aan de financiële sector met als gevolg de ontwrichting van de algehele economie. Academici hebben op dit gebied getracht systeem risico exact te definiëren en te meten. Beleidsmakers trachten te voorkomen dat het vooruitzicht op financiële ondersteuning voor banken niet leidt tot een opzettelijke verslechtering van risico posities. Het publiek houdt zich bezig met systeem risico vanwege de substantiële beroepen die gedaan worden op belasting-

gelden om banken te herkapitaliseren. In de voorgaande hoofdstukken worden deze bovengenoemde perspectieven nader belicht en onderzocht.

In Hoofdstuk 2 wordt het concept *too-connected-to-fail* geïntroduceerd. Met deze classificatie worden banken geduid wiens stabiliteit van cruciale betekenis is voor de stabiliteit van de financiële sector. Echter wordt deze classificatie niet noodzakelijk gedreven door de grootte van de bank, als in de marktwaarde van de activa, maar eerder vanwege de verbondenheid met ander financiële instellingen door middel van bijvoorbeeld kredietbesmetting.

Aangezien het niet mogelijk is de intensiteit van de verbindingen tussen banken waar te nemen worden deze afgeleid en geschat met behulp van Extreme Waarde Theorie. Uit herhaalde substantiële bewegingen in de premies van CDS contracten en rendementen op aandelen leiden we de mate van verbondenheid tussen financiële instellingen af. Een substantiële toename van een CDS premie is indicatief voor een toename op de kans en de kosten van het faillissement van de onderliggende instantie. Op het moment dat twee instanties herhaaldelijk dergelijke toenames in hun CDS premies tegelijkertijd ervaren kan men spreken van een krediet risico verbinding, al dan niet beïnvloed door externe factoren. Een verbinding waarbij het voor kan komen dat als één instantie failliet dreigt te gaan de ander een dergelijk scenario ook waarschijnlijk zal ervaren, visa versa, of tegelijkertijd. Hetzelfde geldt voor negatieve rendementen behaald op het bezit van aandelen. Resultaten geven weer dat naarmate financiële instanties een centrale rol vervullen binnen de financiële sector zij eerder in aanmerking kwamen voor financiële ondersteuning uit belastinggelden ten einde de bank te herkapitaliseren. Dit resultaat is verkregen terwijl rekening is gehouden met de grootte van de instantie en risico factoren die voor de bank specifieke elementen controleren.

In hoofdstuk 3 is het onderwerp van studie de relatie tussen compensatie voor directeuren van financiële instellingen en de formatie van systeem risico in de financiële sector. Resultaten wijzen erop dat met name de grootte van de bonus compensatie voor leden van de bestuursraad die geen voorzitter zijn (non-CEO directeuren) bijdraagt aan de formatie van systeem risico. Dit resultaat sluit aan bij eerdere theoretische bevindingen in de literatuur waarin de voorzitter begaan is met de algehele prestaties van de bank, terwijl de overige directeuren begaan zijn met de prestaties van met name de afdelingen die zij vertegenwoordigen. Die risico's die bijdragen aan de formatie van systeem risico kunnen hierdoor afkomstig zijn van keuzes die gemaakt worden door managers die zich met name bezig houden met risico-rendement afwegingen die de eigen afdeling betreffen. Waar vervolgens door de afdeling risico posities worden ingenomen die worden afgewenteld op andere afdelingen en uiteindelijk op partijen buiten de bank als de bank als geheel failliet dreigt te geraken. Het is daarom van belang dat financiële markt autoriteiten zich niet enkel bezig houden met de grootte van de beloningen voor top mangement, maar ook met de vraag hoe door de beloningstructuur van de bank de belangen en acties van de overige management lagen worden beïnvloed.

In Hoofdstuk 4 worden twee beleidsinstrumenten bestudeerd: een systeem risico belasting en een fonds waarmee herkapitalisering van failliete banken kan worden gefinancierd. Een systeem risico belasting is een nog niet bestaand middel om banken te ontmoedigen bij te dragen aan de formatie van systeem risico, maar wordt op dit moment besproken in de academische literatuur en beleidsvoorstellen. In tegenstelling tot de bestaande literatuur wordt in dit hoofdstuk de afhankelijk tussen beide beleidsinstrumenten gemodelleerd. Deze afhankelijkheid volgt uit het gemeenschappelijke doel waarvoor deze instrumenten worden gebruikt, namelijk het behouden van financiële stabiliteit. Het model laat zien dat het negeren van deze afhankelijkheid kan leiden tot verkeerde interpretaties met betrekking tot de effectiviteit van beide instrumenten. De intuïtie ligt in het signaal dat wordt afgegeven door het zetten van een systeem risico belasting over de mate waarin de overheid begaan is met het behouden van financiële stabiliteit. Dit signaal kan door banken worden gebruikt om nauwkeuriger de kans vast te stellen dat zij in aanmerking komen voor herkapitalisering fondsen gedurende een crisis. Indien deze kans als acceptabel wordt geacht kan deze informatie tot meer systeem risico formatie leiden, terwijl de bedoeling van de belasting was dergelijke risico's juist terug te dringen. Dit resultaat suggereert dat afhankelijkheid tussen beleidsinstrumenten in ogenschouw dient te worden genomen om de effectiviteit van deze instrumenten vast te kunnen stellen.

Hoofdstuk 5 presenteert een krediet risico model waarmee wordt onderzocht in welke mate financiële instellingen baat hebben gehad van mogelijke herkapitalisering fondsen in het vooruitschiet. Het anticiperen van bailout fondsen tijdens een financiële crisis kan leiden tot financieringen voordelen voorafgaand aan de crisis. Dit financieringsvoordeel volgt uit het feit dat crediteuren het risico op faillissement niet langer volledig dragen, maar gedeeltelijk af kunnen wentelen op toekomstige fondsen gefinancierd met belastingen. Krediteuren vragen vanwege dit voordeel een lagere compensatie voor het risico op faillissement. Voor banken werkt deze lagere compensatie door als financieringsvoordeel wat gemeten kan worden met behulp van het gepresenteerde model. Resultaten wijzen erop dat banken inderdaad baat hebben gehad voorafgaande aan de financiële crisis van 2007/2008. Dit blijkt uit de empirische relatie tussen de geschatte garanties van de overheid op de schulden van banken voorafgaande aan deze crisis en de bailouts die zijn uitgekeerd ten tijde van de crisis.